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Optimal Design and Control of Electric Traction Systems for Efficiency and Handling Enhancement in Battery Electric Vehicles

By

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Declaration

I hereby declare that, the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Raffaele Manca
2025

* This dissertation is presented in partial fulfillment of the requirements for **Ph.D. degree** in the Graduate School of Politecnico di Torino (ScuDo).

Ai miei genitori

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Abstract

The transition to electric powertrains drives innovation in vehicle design and control, leading to the new generation of sustainable and safe mobility solutions. Electrification offers flexibility in powertrain architectures, from single onboard motor vehicle to multi-actuated systems with in-wheel motors. This doctoral thesis presents user-centered optimization methodologies for both the design and control of electric traction systems in various powertrain configurations, addressing optimization at the component level and extending to the vehicle-level control. The thesis is organized around three main areas.

Firstly, a comprehensive design methodology based on multiple driving cycles is proposed to optimize an innovative electric drive module (EDM) for reconfigurable, low-voltage battery electric vehicles, using a multi-objective genetic algorithm (MOGA). This work covers the detailed design, modeling, and prototyping of a multi-phase electric motor powered by a dual-inverter system with a modular, swappable battery pack.

Secondly, a preview-based Nonlinear Model Predictive Control (NMPC) is developed to enhance traction control on irregular road surfaces by utilizing data on upcoming road profiles and friction conditions. Simulation analysis and experimental validation demonstrate that, thanks to the rapid torque response of electric motors integrated with information from exteroceptive sensors and V2X communication, the proposed control strategy improves tire slip control across various road scenarios.

Lastly, multi-motor powertrain architectures allow for centralized torque control strategies that enhance vehicle handling, safety, and efficiency. A predictive torque vectoring control for electric vehicles with in-wheel motors is proposed, combining predictive state feedback and feedforward control with estimation algorithms of non-measurable variables. The approach is evaluated through simulation and track testing.

Overall, the findings highlight the potential of electric powertrains to redefine vehicle performance and efficiency through optimized design and intelligent control strategies.

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Chapter 1

Introduction and background

1.1 Vehicle electrification: challenges and opportunities

The electrification of road transportation is a cornerstone of global efforts to mitigate climate change and achieve carbon neutrality. The transportation sector contributes for approximately 15% of global greenhouse gas (GHG) emissions [1], with road transportation accounting for 96% of this share in Europe [2]. The electrification of road vehicles offers a viable path to decarbonize this sector, supported by technological advancement, regulatory framework, and growing environmental awareness.

Around the world, governments have established ambitious targets to reduce emissions and promote electric mobility. The European Union's "Fit for 55" program mandates a 55% reduction in GHG by 2030 and bans the sale of internal combustion engine (ICE) vehicles from 2035, with the exception of those fueled with e-fuels. [3]. The US 2050 Net Zero CO₂ Plan is a long-term strategy to reduce GHG emissions in the United States, through tax incentives and government grants [4], despite ongoing discussions regarding the possible U.S. withdrawal from the Paris Agreement. Meanwhile, China under its New Energy Vehicle (NEV) policy, is targeting a 20% reduction in CO₂ in the transportation sector by 2035 [5]. These global efforts are complemented by regional policies and incentives. However, progress varies significantly between regions, reflecting differences in infrastructure, income levels, and policy intensity [6].

Electric vehicles (EVs) include a range of degrees of electrification, and powertrain technologies. The level of electrification for given vehicles defines the ratio of electrical power available to total power [7]. Hybrid Electric Vehicles (HEVs) allow the combination of two different energy sources, i.e. a fuel tank and a battery, combining ICEs with electric motors, achieving up to the 50% degree of electrification. Plug-in Hybrid Electric Vehicles (PHEVs) extend the range of HEVs and the overall fuel efficiency. PHEVs allow for external charging, allowing them to operate the car in the battery-only mode for a long time until the battery is almost completely depleted. Both HEVs and PHEVs represent a fundamental step in the progressive paradigm shift toward transportation electrification; however, they exhibit intrinsic complexity due to the simultaneous presence of multiple energy sources. This requires the implementation of effective energy management strategies, addressing challenging packaging constraints, and integrating complex transmission mechanisms [8]. On the other hand, in battery electric vehicles (BEVs) the traction power is supplied solely from an electric motor and an electric energy storage system (ESS), achieving the maximum level of fuel efficiency. One of the main concerns in BEVs is the limited driving range, which is dependent on the energy density of the battery system [9]. Fuel Cell Electric Vehicles (FCEVs), exploit hydrogen as an energy carrier, FCEVs offer high range and quick refueling, making them ideal for heavy-duty applications, although challenges remain in terms of hydrogen production and infrastructure [10]. This analysis focuses on Battery Electric Vehicles (BEVs), as they represent the most advanced solution in terms of energy efficiency, zero tailpipe emissions, and reduced dependence on fossil fuels. Unlike other electrified powertrains, BEVs maximize the integration of renewable energy sources and simplify vehicle architecture by eliminating the complexity of multiple energy sources [11].

Dealing with market penetration, in 2024, global EVs sales reached 17.1 million units, representing approximately 20% of total car sales worldwide. BEVs accounted for the majority of these sales, highlighting the continued global shift toward full electrification. China remains the dominant player, with nearly 11 million units sold, capturing approximately 64% of the global EV market. This growth is driven by strong government incentives, an extensive charging infrastructure, and a mature domestic supply chain. In contrast, Europe experienced a slight decline, with sales totaling 3 million units, reflecting a 3% contraction due to reduced subsidies in key markets like Germany, which saw a 27% drop. North America showed

moderate growth of 9%, with EV sales reaching 1.8 million units, while other regions collectively contributed 1.3 million units, growing by 27% [12].

Despite these positive trends, significant challenges remain in achieving large-scale adoption. Key barriers include insufficient charging infrastructure in many regions, high upfront costs for purchasing BEVs, and persistent consumer concerns such as range anxiety. These factors continue to limit the penetration of BEVs. In Figure 1.1 the number of EVs registered and the market share are reported, per geographic area [13].

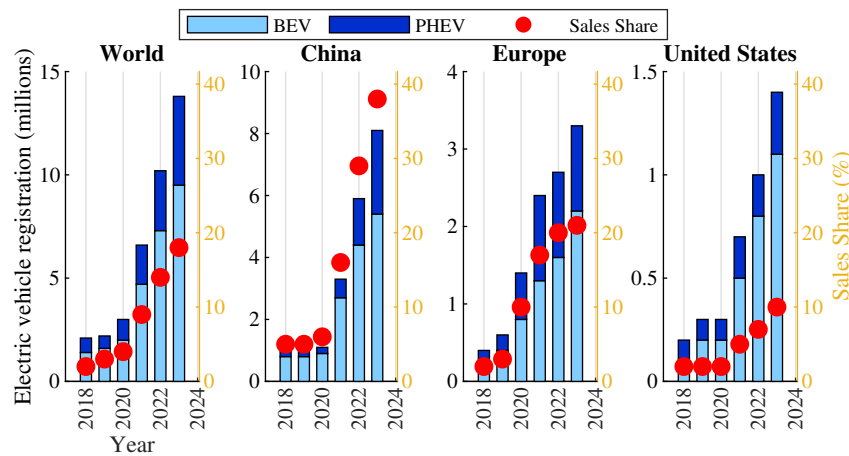


Fig. 1.1 Electric car registrations and sales share in China, United States and Europe, 2018-2023.

Electric powertrains, however, represent a transformative shift in vehicle design and functionality. Their modularity supports a wide range of configurations, including dual- and quad-motor systems that enhance handling, energy efficiency, and stability. Regenerative braking systems can recover up to 30% of dissipated energy during deceleration, while torque vectoring dynamically adjusts power distribution across wheels for improved performance [14]. Moreover, the integration of electric powertrains with advanced electronic controls, exteroceptive sensors, and vehicle-to-everything (V2X) connectivity enables assisted and automated driving features, paving the way for the next generation of sustainable and intelligent mobility [15].

1.2 Powertrain architectures for BEVs

Current electric vehicle research is investigating different powertrain configurations constituted by single or multiple motors, with different characteristics and possibilities to optimize efficiency and vehicle dynamics performances [14, 16]. Unlike internal combustion engine vehicles, which rely on a centralized power source and a complex transmission system, BEVs benefit from greater flexibility in powertrain design. Various powertrain architectures have been proposed and implemented, each with its own advantages and trade-offs.

- **Single-motor centralized drive**

Single-motor architectures remain the most common and cost-effective configuration for BEVs. In this design, a single electric motor powers either the front (front wheel drive - FWD) or rear axle (rear wheel drive - RWD) through a transmission system and differential. The transmission systems are generally single-stage, multi-stage gear reducers, or continuously variable transmission (CVT) [17]. This setup is widely used in mass-market vehicles due to its mechanical simplicity and lower cost [18]. Examples of commercial vehicles that use this architecture include the Nissan Leaf, Tesla Model 3 RWD, and Chevrolet Bolt [19]. However, this layout limits advanced control capabilities in stability control and energy management, compared to multi-motor configurations.

- **Dual-motor configurations**

Dual-motor coupling powertrain systems exploit two motors to realize multiple drive modes and utilize several mechanical coupling mechanisms to properly distribute the power of the two EMs to improve the overall efficiency. Dual-motor powertrains can enhance efficiency by maintaining both motors within their optimal operating regions through the application of torque and speed coupling or decoupling. This strategy enables the selection of the most efficient operating points based on a combined efficiency map [20]. Dual-motor BEVs are typically categorized into traction-coupling, torque-coupling, and speed-coupling architectures [21]. Traction-coupling or axle-split dual-motor Drive, as exemplified by Tesla's Model 3 AWD (all-wheel drive), Hyundai's e-GMP platform, and Porsche Taycan, employs distinct front and rear e-axes to facilitate independent control and enhanced traction.

Torque coupling in dual-motor powertrains connects two motors via a gear system, allowing their torque outputs to be combined while maintaining a proportional speed relationship. A common challenge is the increased packaging volume due to parallel shaft placement. To address this, Zhu et al. [22] propose a coaxial arrangement, where one motor engages only during high torque demands, using a hollow rotor to reduce size and a one-way clutch to prevent drag losses. Similarly, [23] suggests a coaxial dual-motor setup on opposite sides for improved compactness. Alternatively, planetary gear-based coupling provides a balance between efficiency and packaging constraints.

In a speed-coupling architecture, the output speed is a weighted sum of the two motor speeds, while the output torque is proportional to the torque of both motors. These systems are mainly classified into planetary gear speed coupling and differential speed coupling, with the former being more common [24]. In planetary gear speed coupling, the motor shafts are mechanically connected to either the sun gear, ring gear, or planet carrier, enabling power output from one or both motors via band brakes or clutches.

Beyond these three main categories, the literature also includes multi-mode (or mixed-coupling) architectures that combine elements of torque and speed coupling within a single system, thus broadening the high-efficiency operating range under varying driving conditions [25]. Torque, speed, and mixed coupling, while extensively investigated in academic literature, remain primarily at a conceptual or prototype stage for full BEV applications [21, 26]. Additionally, dual-motor configurations on a single axle (left-right split) facilitate advanced torque vectoring [27]. Some manufacturers further leverage different motor types (e.g., induction vs. permanent magnet) or distinct transmission ratios on the front and rear axles to optimize efficiency and performance across a wider range of speeds and loads, while maintaining a fully electric powertrain.

- **Four-motor distributed drive**

The quad-motor architecture represents the state-of-the-art of performance-oriented BEV powertrains. In this setup, each wheel is powered by an independent motor, enabling precise torque vectoring and superior handling control [28]. This architecture eliminates the need for conventional differentials, enhancing both traction and lateral dynamics performances. The Rimac Nevera, Lotus Evija, and Rivian R1S are examples of vehicles adopting this approach.

Although this architecture offers better traction and torque vectoring capabilities, it also presents challenges related to cost, weight, and power electronics complexity.

- **In-wheel motors**

A more radical approach is the adoption of in-wheel motors (IWMs), where electric motors are integrated directly into the wheel hubs. This eliminates the need for a traditional transmission and differential, reducing drivetrain losses and improving packaging efficiency [29]. Some companies, such as Elaphe, Protean, QS Motor, and Schaeffler, have developed commercially available in-wheel motor solutions.

Vehicles such as the Lightyear One and Lordstown Endurance have experimented with this technology, although its widespread adoption has been limited due to challenges in managing increased unsprung mass, heat dissipation, and durability under real-world conditions [30]. Furthermore, in-wheel motor configurations can suffer from reduced efficiency at low-speed high-torque conditions, making them still less favorable for mainstream automotive applications [31].

In figure 1.2 six examples of BEVs powertrain layouts with one to four electric drive modules (EDM), are depicted.

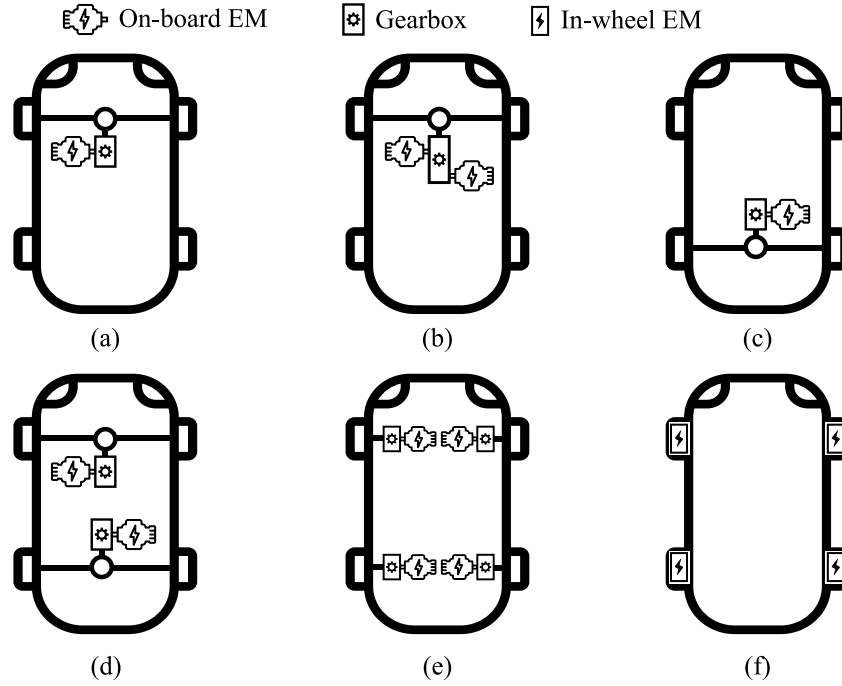


Fig. 1.2 Examples of BEVs architectures with one to four electric drive modules: (a) FWD single-motor; (b) FWD dual-motor, torque/speed-coupling; (c) RWD single-motor; (d) AWD dual-motor traction-coupling; (e) AWD on-board four-motor distributed drive; (f) AWD in-wheel four-motor drive.

Beyond traditional powertrain architectures, academic and industrial research is increasingly exploring unconventional and innovative solutions, such as modular powertrain architectures. A novel reconfigurable battery electric vehicle, developed by the author's research team, will be analyzed in 2.

1.3 Topologies of electric motors for traction application

Several governmental agencies have set the current and future performance targets for electric traction motors. For example, the electrification roadmap of the European Transport Research Advisory Council (ERTRAC) sets motor-to-wheel efficiency target ranges for 2030 of 87-92% along the worldwide harmonized light vehicles test procedure (WLTP), while the US Department of Energy (DoE) sets targets for EV traction machines, to be achieved by 2025. The DoE document states that the 2025

baseline peak and continuous power values were, respectively, increased to 100 kW and 55 kW, with 650 V battery voltage and 600 Arms inverter current [32].

In general, the selection of the electric machine for traction application should satisfy key performance indicators (KPIs), including:

- High efficiency across a wide speed and torque range to minimize energy consumption and extend vehicle range [29, 17].
- High power and torque density to ensure compact and lightweight designs while maintaining high performance [33].
- High torque capability at low speed for acceleration and hill climb performance.
- Robust field-weakening capabilities to allow extended speed range operations.
- Reduced dependency on rare-earth materials.
- Excellent thermal management to maintain high efficiency and durability [34].
- Minimal torque ripple and acoustic noise to enhance vehicle comfort and drivability [35].
- Manufacturability and cost-effectiveness, ensuring economic feasibility for mass production.

These requirements necessitate an accurate analysis of available electric motor topologies, each of which presents unique advantages and trade-offs. Moreover, the development of tailored design methodologies for selecting electric motor parameters is essential to maximizing efficiency and achieving the aforementioned targets, particularly within the required operational range, while ensuring compliance with design constraints. This challenge can be effectively addressed through advanced optimization techniques integrated with electromagnetic, thermal, and multi-physics models [36].

EVs were initially equipped with DC traction motors since they showed reasonable performance curves and ease of controllability. However, although DC motors are still relevant in micro-mobility applications, their limitation in maximum speed, lower efficiency, and power density due to brushes and commutators, make them unfeasible for modern BEVs [37].

Brushless motors, on the other hand, offer greater efficiency and reliability. The main topologies for EV traction applications are induction machines (IM), permanent magnet synchronous motors (PMSM), switched reluctance motors (SR), wound rotor synchronous motors (WRSM), and axial-flux motors (AFM). In Fig. 1.3 a qualitative comparison of the possible topologies of electric motors for traction application in BEVs is reported.

In addition to motor topology, winding technology significantly impacts efficiency, thermal performance, and manufacturability. Hairpin windings, which use flat rectangular conductors instead of round wires, enhance slot fill factor, thermal dissipation, and efficiency, making them ideal for high-performance PMSMs and WRSMs [29]. While they reduce copper losses and improve power density, skin, and proximity effects can increase losses at high switching frequencies, requiring optimized designs and advanced cooling strategies. Automakers like Toyota and General Motors have adopted hairpin winding technology.

The next subsections cover the main characteristics of EMs topologies.

1.3.1 Induction motors (IM)

Induction Motors operate through electromagnetic induction, eliminating the need for permanent magnets or brushes. They offer robust performance, high reliability, and lower material costs [38]. However, their overload capability is limited by the important heat dissipation in the rotor. The concern of IMs is the low efficiency at low speeds, due to rotor copper losses [39]. IMs exhibit excellent performance in applications requiring high torque at low speeds [40], like heavy-duty vehicles, stop-and-go traffic, and off-road driving scenarios. Audi, Hyundai, and some Tesla configurations opted for induction motors.

1.3.2 Permanent magnet synchronous motors (PMSM)

Permanent Magnet Synchronous Motors are the predominant choice for modern BEVs, consistently exceeding a 75% market share [41] due to their high efficiency, power density, and torque density [42]. They use permanent magnets, typically rare-earth-based - specifically NdFeB - to generate a strong and continuous magnetic field, eliminating the need for rotor excitation windings. In Permanent Magnet

(PM) machines, copper losses are predominant at lower speeds, whereas iron losses become more significant as the speed increases. Additionally, under flux weakening conditions, the impact of harmonic iron losses due to PM-induced magnetic fields becomes more pronounced. Although rotor losses are generally minor compared to stator copper and iron losses, they are not negligible, particularly in high-frequency scenarios, such as at elevated speeds or with a high number of poles [43].

One major limitation of PMSMs is their reliance on rare-earth materials, which are subject to price volatility and geopolitical constraints. Efforts are being made to develop rare-earth-free PMSMs using ferrite magnets or hybrid excitation techniques [44].

Surface permanent magnet (SPM) machines

SPM machines feature magnets mounted on the rotor surface, offering simple construction, and low copper losses at low speed. However, they exhibit limited field-weakening capabilities and significant eddy current losses in the magnets, particularly at high speeds [45]. Generally, in-wheel motors feature SPM outrunner configurations.

Interior permanent magnet (IPM) machines

IPM machines incorporate embedded magnets within the rotor structure, enhancing field-weakening capabilities and providing additional reluctance torque. This results in improved efficiency across a wider operating range, making IPMs the preferred topology for high-performance BEVs [46]. However, their increased rotor complexity poses manufacturing challenges and raises costs.

The rotor PM arrangement plays a crucial role in minimizing losses in IPM machines, with V-shaped, tangential, and delta-shaped configurations commonly used in commercial EVs. While V-shaped and tangential arrangements offer high efficiency and low torque ripple, respectively, delta-shaped designs, as seen in the Nissan Leaf and Toyota Prius, enhance reluctance torque and flux weakening but with lower efficiency in the flux weakening region. Proper design of the magnetic bridge width and flux barriers is essential to balance efficiency, harmonic effects, and mechanical strength [29, 47].

The PM-assisted synchronous reluctance machines (PMaSynR) can be considered as an IPM with high saliency and low PM usage, with the advantages of a wider speed range at constant power and relatively lower cost. The PMaSynR machine derives from the synchronous reluctance (SynR) machine, by inserting PMs into the rotor flux barriers. The loss components are similar to those of IPM machines, with the exception of the PM eddy-current loss, which is less significant because of the reduced PM volume [48].

1.3.3 Switched Reluctance Motors (SRM)

Switched Reluctance Motors rely on rotor saliency and variable reluctance principles to generate torque. Their simple, magnet-free construction results in low manufacturing costs [17, 46].

SRMs offer high torque at low speeds and a broad constant power range, eliminating the need for additional transmission systems. Their simple structure and low rotor inertia enable fast dynamics, but NVH issues and complex electronics limit their commercial adoption in EVs. Despite this, ongoing research supports SRMs as a viable alternative to PM and Induction Motors [49].

1.3.4 Wound Rotor Synchronous Motors (WRSM)

WRSMs use rotor windings energized via slip rings or wireless excitation to generate a controllable magnetic field, eliminating the need for permanent magnets. These machines provide excellent field-weakening capabilities and precise control over excitation currents [50].

Recent developments by Renault and BMW have focused on WRSMs as a viable alternative to PMSMs, aiming to achieve high efficiency while avoiding rare-earth material dependencies. However, the additional complexity of rotor excitation systems remains a challenge for large-scale adoption.

1.3.5 Axial-Flux Motors (AFM)

Axial-flux motors, feature a disc-shaped stator and rotor, resulting in a shorter axial length and higher torque density compared to radial-flux designs. These machines offer significant weight savings and packaging advantages.

While AFMs have demonstrated high performance in niche applications, challenges related to manufacturability, thermal management, and mechanical robustness have hindered widespread adoption [51].

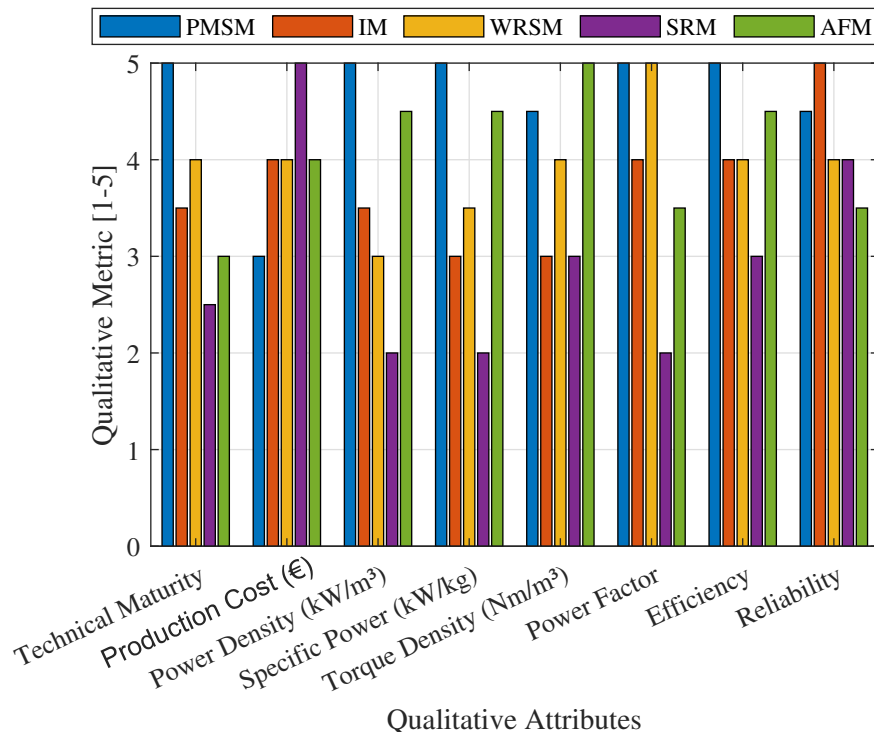


Fig. 1.3 Qualitative evaluation of different attributes for electric motor topologies [17].

1.4 Control of electric traction systems to improve handling, safety, and efficiency

The shift towards electric powertrains has unlocked new possibilities for advanced vehicle control strategies, leveraging the fast and precise torque response of electric motors compared to internal combustion engines [46]. At the low-level motor control stage, strategies such as Field-Oriented Control (FOC) and Direct Torque Control

(DTC) ensure precise and high-bandwidth torque actuation, optimizing motor efficiency and responsiveness. More advanced approaches, such as Model Predictive Control (MPC), use real-time system predictions to enhance performance across different operating conditions. However, the true potential of electric powertrains extends beyond motor-level control. Thanks to their fast and independent torque generation, electric motors enable a paradigm shift where the powertrain itself acts as an actuator for vehicle dynamics, actively influencing stability, handling, and efficiency, leading to a vehicle-level control approach. This capability is particularly beneficial for applications such as traction control systems (TCS) [52], anti-jerk controllers [53], stability controllers [27], and control strategies that enhance ride comfort [54]. Additionally, multi-motor layouts provide an additional degree of freedom to improve vehicle dynamics, active safety, and overall system efficiency by leveraging independent electric machine control and optimizing torque distribution, such as in torque-vectoring (TV) strategies [55].

Traction Control Systems prevent excessive wheel slip by modulating wheel torque, ensuring stability and grip. In ICE vehicles, TCS relies on throttle, injection, or ignition intervention or on friction brakes, while electric powertrains enable much faster and more precise torque adjustments, improving performance across various road conditions. Similarly, Antilock Braking Systems (ABS) can exploit electric motors for regenerative braking, reducing full reliance on friction brakes. However, since electric machines provide limited braking torque at very low speeds or insufficient power for demanding braking scenarios, blended braking strategies are typically adopted. These strategies combine regenerative and friction braking to ensure effective deceleration [56]. Control strategies for TCS and ABS range from rule-based PI controllers, which provide simple but reactive responses, to slip ratio controllers, which dynamically adjust torque based on tire-road friction estimation [57]. More advanced solutions, such as Nonlinear Model Predictive Control (NMPC), anticipate traction loss and optimize torque modulation using real-time road condition data [53].

Torque vectoring is another fundamental control strategy enabled by multi-motor electric powertrains, allowing for independent wheel torque allocation to generate yaw moments that enhance cornering stability and agility. Unlike brake-based yaw control, which dissipates energy, TV redistributes power efficiently and ensures a faster yaw response [28, 27]. Research on optimal TV control has demonstrated that yaw control can be designed not only for stability but also to minimize powertrain

losses, improving power usage in both straight-line driving and cornering [58, 59]. Furthermore, TV can be beneficial for autonomous driving applications, improving path-tracking capabilities [60].

Electric powertrains also enable active control strategies that enhance comfort and drivability through precise torque modulation. Unlike traditional passive systems, active control in electric vehicles can mitigate longitudinal acceleration oscillations caused by road irregularities, improving comfort [61]. Applications include anti-jerk control [53], which smooths abrupt torque variations, and pitch minimization, which reduces vehicle oscillations during acceleration and braking, particularly effective in in-wheel motor architectures due to their fast response time [62]. Predictive NMPC strategies further enhance ride comfort by leveraging road preview data, achieving over 80% reduction in longitudinal oscillations, leading to a more stable and controlled driving experience [54].

By treating the powertrain not only as a source of propulsion but also as an actuator for vehicle dynamics, BEVs can achieve superior agility, safety, comfort, and energy efficiency. Future developments will further integrate AI-based predictive control, vehicle-to-everything connectivity, and integration with advanced driver assistance system (ADAS) exteroceptive sensors, enabling real-time adaptive control strategies that enhance overall vehicle performance.

1.5 Objectives, and original contribution

The transition to electric powertrains fosters innovation in both vehicle design and control strategies, paving the way for more efficient and sustainable mobility solutions. Electric drivetrains enable innovative powertrain architectures, such as modular and reconfigurable systems, offering greater flexibility to adapt to different driving scenarios and user demands. Advanced control strategies fully leverage the potential of electric traction systems across various layouts, optimizing performance, stability, and energy efficiency at the vehicle level. The integration of electrified systems with optimization methods in both design and control allows for comprehensive improvements in overall vehicle performance.

This thesis aims to develop optimization methods for the design and control of propulsion systems in battery electric vehicles. In this context, several research questions emerge as pivotal points of this work:

- How can we promote the diffusion of urban electric mobility by developing user-centered, reconfigurable vehicle architectures? What is the most suitable electric traction system topology to enable this flexibility?
- Is it possible to develop a comprehensive optimal design methodology for an electric drive module (EDM) in a reconfigurable vehicle, enhancing efficiency at the vehicle level by considering multiple driving missions?
- In on-board powertrain architectures, can real-time optimal control strategies integrate information from sensors and communication networks to improve traction control performance?
- In multi-motor architectures, can safety and agility be simultaneously enhanced through real-time deployable torque vectoring control strategies?
- Can torque vectoring control strategies contribute to improved efficiency at the vehicle level?

To address these questions, this research proposes the following objectives:

- Develop a comprehensive design methodology based on multiple driving cycles, aimed at optimizing an innovative electric drive module for a reconfigurable, low-voltage BEV application.
- Investigate how a preview-based Nonlinear Model Predictive Control strategy can improve traction control of BEVs, on irregular road surfaces by leveraging future road profile information and real-time friction estimation.
- Explore how to enhance both stability and agility in electric vehicles equipped with in-wheel motors using a predictive torque vectoring control strategy that eliminates the need for dedicated real-time solvers.

1.6 Outline of the dissertation

This dissertation is structured into five chapters as follows:

- Chapter 1 – Introduction: Introduces the context and motivations of the research, emphasizing the role of electrified mobility and outlining the main research questions addressed throughout the thesis.
- Chapter 2 – Optimal design of electric drive module for reconfigurable vehicle: Presents a novel multi-objective design methodology for a dual-inverter six-phase IPM machine intended for urban electric vehicles. The method includes FEM-based electromagnetic and thermal analysis, and uses driving-cycle performance indicators as optimization targets.
- Chapter 3 – Preview based traction control system for battery electric vehicles: Describes the development of a nonlinear model predictive control (NMPC) strategy for traction control, incorporating road preview and road friction estimation.
- Chapter 4 – Torque vectoring for battery electric vehicles: Focuses on predictive torque vectoring strategies for dual- and quad-motor architectures. An energy-conscious torque distribution algorithm (ECO allocator) is proposed, as well as a sideslip angle estimation algorithm.
- Chapter 5 – Conclusions and Future Work: Summarizes the key findings, providing answers to the research questions and outlining future developments.

Chapter 2

Optimal design of electric drive module for reconfigurable vehicle

The shift toward sustainable transportation systems in urban areas should extend beyond conventional battery electric vehicles. Although urban electric mobility is on the rise, several challenges remain to improve market penetration, such as the high purchase cost of BEVs and range anxiety. Increasing battery capacity may alleviate range anxiety but also raises vehicle cost and weight [63]. Additionally, the rising cost of raw materials further complicates affordability and adoption [64]. This push for larger batteries seems mismatched with the daily driving habits in Europe, where the average driver covers about 40 km per day [65]. Consequently, heavier, more expensive battery packs might not satisfy actual user needs and could undermine the economic and environmental benefits of electrification.

At the same time, micro-mobility and shared mobility solutions have emerged as promising alternatives, enabling flexible charging options while reducing congestion and emissions in city centers. In response to these evolving demands, L-class vehicles have gained popularity due to their lower cost compared to traditional M-class passenger cars [66]. Their compact dimensions make them well-suited for short-range urban trips, allowing for easier parking and maneuverability in congested environments. However, they typically lack sufficient power and range for extra-urban missions, and they are not subject to the same passive and active safety standards as M-class vehicles [67, 68].

In this context, there is a clear need for an affordable, sustainable vehicle primarily intended for urban use yet reconfigurable for extra-urban missions. This vehicle should retain the low-voltage characteristic of an L-class design while incorporating the safety, range, and performance features of M-class cars. To address this gap, a low-voltage reconfigurable electric vehicle (LVREV) is proposed, which bridges the gap between these two categories [69].

This activity has been developed in the framework of collaboration of MOST - Centro Nazionale della Mobilità Sostenibile, Spoke 2 [70].

2.1 Reconfigurable electric vehicle architecture definition

The overarching principles according to which the LVREV is designed are:

- *Modular* - The LVREV concept features a modular battery swap system consisting of two independent modules.
- *Tailored to user* - Each battery module can be loaded onboard independently according to the user's needs, and the proprietary reconfigurability/power distribution box will reconfigure the powertrain architecture accordingly.
- *Safe and affordable* - The low voltage system (<60 V) allows to perform manual battery swap operations without requiring specialized equipment or skilled personnel [68]. Furthermore, electrical elements, like minus and on-module contactors can be removed due to the safe-low voltage architecture, simplifying the overall electric architecture.
- *Home integrated* - The battery modules can be integrated with domestic energy accumulators.

2.1.1 Vehicle target setting

According to the benchmarking analysis of the L and M vehicle categories available on the market, reported in [69], two vehicle configurations are defined. The Frugal version is intended for urban missions, with performance parameters and range

Table 2.1 Target settings for Frugal and Dual vehicle configurations

Vehicle configurations	Frugal	Dual
Top speed	≥ 90 km/h	≥ 130 km/h
WLTC-city Range	≥ 150 km	-
Voltage	≤ 60 V	≤ 60 V
Curb weight	≤ 900 kg	≤ 1000 kg
Climbing 15 km/h slope	20%	20%
Acc. time 0 - 50 km/h	≤ 6 s	≤ 6 s (0 - 60 km/h)
Acc. time 0 - 90 km/h	≤ 19 s	≤ 14 s (0 - 100 km/h)

tailored to city commuting. In keeping with most L-category vehicle specifications, it targets 150 km of range on the WLTC-City cycle and a top speed of 90 km/h, which matches the maximum velocity used in that cycle. The vehicle's weight limit is set at 900 kg. To the best of the author's knowledge, this represents the best trade-off among the power required for motion on the driving cycle, the output capacity of a low-voltage powertrain, load capability, and passive safety standards.

By contrast, the Dual configuration aims to offer range and performance features comparable to those of an A segment M-class vehicle, thus enabling extra-urban use. Table 2.1 summarizes the targets of both configurations. Its range requirement exceeds 200 km on the WLTC, which leads to a weight limit of 1000 kg to accommodate the larger battery pack necessary for operating at speeds of at least 130 km/h. Moreover, because of the low-voltage constraint, carrying out the WLTC and WLTC-City missions needs currents on the order of hundreds of amperes. Therefore, it becomes crucial to adopt technological solutions that reduce the load on the DC bus, particularly in extra-urban scenarios requiring higher power.

DC bus voltage selection

The selection of a 48 V DC bus voltage for the proposed electric powertrain architecture reflects a trade-off between regulatory compliance, user-centered design, and powertrain complexity. In accordance with IEC 61140 and ISO 6469-3 [71, 72], electric systems operating below 60 V DC fall within the Safety Extra Low Voltage (SELV) class. This classification removes the need for reinforced insulation, strict creepage and clearance distances, and high-voltage monitoring and interlock systems. As a result, the adoption of a SELV architecture allows the user to perform manual

battery swapping safely, simplifies the design of the on-board charging system, allowing direct connection to the residential AC grid. Furthermore, operating in the SELV range eases homologation procedures, particularly for light vehicle categories.

This choice is consistent with the objectives of L6e and L7e category vehicles, which are typically constrained by strict weight and cost requirements. Most applications in these classes operate in the 48–60 V range, thus avoiding the constraints associated with high-voltage traction systems [73].

Nevertheless, the main drawback of low-voltage operation lies in the elevated current levels required to meet power demand. For instance, delivering more than 20–30 kW on a 48 V bus may result in current peaks well above 400 A. This significantly affects conductor sizing, converter losses, and overall thermal management.

In this context, the powertrain design choices adopted in the LVREV are conceived specifically to address such challenges while preserving the advantages of operating within the SELV class.

In contrast, high-voltage powertrains, such as 400 V or 800 V systems, offer advantages in terms of reduced cable cross-sections and lower resistive losses, due to significantly lower current levels for the same power output. However, these benefits come at the cost of more stringent regulatory requirements, including continuous insulation resistance monitoring, high-voltage interlock loops, reinforced isolation of components, and the obligation to adopt safety procedures and personal protective equipment for servicing. Therefore, while HV systems are often the preferred choice for full-size electric vehicles with long-range and fast-charging requirements, the low-voltage approach adopted in this work is better suited to modular and affordable urban electric mobility.

2.1.2 Powertrain architecture

Figure 2.1 depicts the proposed 48 V powertrain architecture. The system comprises a modular battery pack, featuring two swappable battery modules, and a dual-inverter arrangement linked to a dual three-phase electric motor [69]. Each battery module includes only the cells and a slave wireless Battery Management System (wBMS), while the master wBMS resides in the on-vehicle reconfigurability switch box and communicates with the modules via a proprietary wireless network.

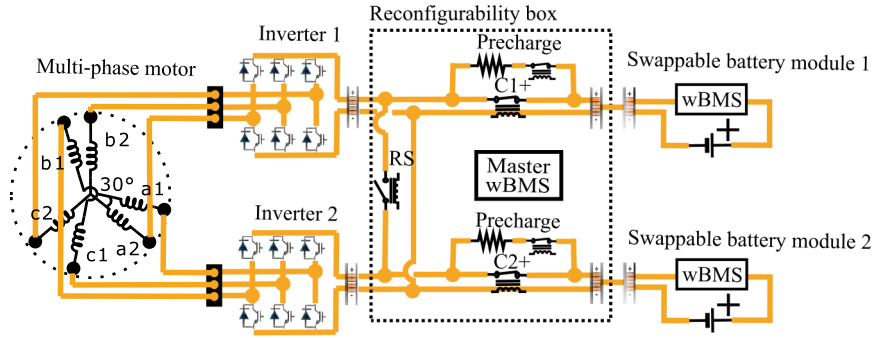


Fig. 2.1 Low voltage reconfigurable vehicle, powertrain architecture.

Since the design operates under safe low-voltage conditions, the positive contactors for the two modules (C1+ and C2+) are housed in the reconfigurability box rather than the modules themselves. This box also encloses the pre-charge circuits, the reconfigurability switch (RS), and the master BMS. The RS switch is controlled by a hardwired logic that allows closure only if one of the two battery module interlocks is open, thus preventing undesired parallel connection of modules. The master BMS coordinates the contactors and the switch to transition between operating modes, described as follows.

Frugal Mode is used when a single battery module is onboard. The switch RS remains closed, so that one battery module supplies both inverters simultaneously, albeit with constrained power output limited by the single module's discharge capability.

Dual Mode is activated when both modules are installed and RS is open, keeping the two DC buses galvanically isolated. Each inverter is then powered by its own module and connected to one three-phase set of the motor. The inverters share rotor-angle information for synchronized six-phase operation. This approach avoids parallel battery connection and thus prevents balance problems. If one module's State of Charge (SoC) drops below a threshold, the system switches back to Frugal Mode by closing RS and opening the discharged module's contactor, leaving the remaining module to power both inverters.

This reconfigurability not only matches the vehicle's energy and performance needs to different missions but also offers redundancy and fail safe operations.

In this framework, optimizing the electric drive module (including the dual-inverter system, the multi-phase electric motor, and the gear reducer) is paramount.

Achieving M-class vehicle performance while remaining below 60 V requires a multi-phase drive [74]. As a first prototype, the proposed powertrain will be integrated into the chassis of a Fiat 500e. The original battery system will be replaced by swappable battery modules, and the EDM will fit within the original mounting envelope of the Fiat 500e's power unit. The single speed gear reducer is iteratively defined according to components availability and installation constraints, consistently with the original 500e reducer layout.

Meeting the vehicle requirements in Table 2.1, along with functional and packaging constraints, calls for an appropriate design methodology to maximize efficiency at the vehicle level. Moreover, the multiple driving missions and reconfigurability features introduce additional challenges for EDM development that must be addressed.

2.2 Electric motor design methodologies: state of the art analysis

Recent advances in electric machine design have been enabled by the rapid growth of electrified mobility, particularly for traction applications in passenger and commercial vehicles. This section discusses the main trends in modeling approaches, simulation tools, and modern optimization techniques that together shape electric machine design.

2.2.1 Modeling and Simulation Approaches

Analytical and Semi-Analytical Models. Traditionally, electric machine design begins with quick analytical formulas or lumped-parameter magnetic circuit analysis. These methods provide fast insights into torque or loss behavior, but often fail to capture non-linear saturation or localized eddy currents. Despite these limitations, analytical approaches remain highly relevant for initial feasibility studies [75].

Finite-Element Methods (FEM). To handle non-linearities in interior permanent magnet (IPM) motors or multi-phase topologies, two- or three-dimensional FEM can be employed. This ensures accurate handling of magnetic saturation, localized losses, and demagnetization risks [76]. Multi-physics co-simulation can capture

electromagnetic, thermal, and mechanical considerations to better deal with the system's constraints [77]. FEM can be coupled with thermal models or lumped-parameter networks to ensure that rotor and winding temperatures remain within permissible limits during extended drive cycles [78]. Rotor stress evaluations can be exploited to avoid critical resonances or mechanical failure [79]. The conventional direct optimization method employs FEM models in the design phase (such as FEM and thermal network model) to evaluate the objectives and constraints in the model and optimizes the required parameters. This co-simulation method can be implemented by integrating MATLAB and Ansys, i.e., using MATLAB to call the Ansys MotorCAD, in the optimization or iterative design program.

2.2.2 IPM design methodologies

Deterministic methods and design variables. Early optimization attempts for IPM designs often relied on deterministic or gradient-based approaches (Sequential Quadratic Programming, Conjugate Gradient) [80]. These methods typically targeted a single, nominal operating point, refining rotor geometry or magnet dimensions iteratively. However, IPMs present strong nonlinearities and saturations, thus deterministic methods are prone to local minima.

When designing IPMs, the design variables are generally geometric features of the rotor (rotor barrier angles, magnet thickness, rib widths), stator dimensions (slot opening, tooth tips), and winding details (turns, wire gauge). The resulting cost function merges average torque, efficiency, torque ripple, thermal constraints, rotor stress, and possibly raw material cost or magnet mass [81].

Evolutionary and multi-objective algorithms. Nature-inspired algorithms, particularly Genetic Algorithms (GAs), are optimization methods that simulate evolutionary principles, making them well-suited for complex engineering design problems. Each GA run starts with a population of candidate solutions, which are assigned fitness values based on the objectives. Solutions with higher fitness are more likely to be selected as “parents” and, via crossover and mutation, produce offspring for the next generation. Typically, a few of the top-performing solutions are also cloned (i.e., preserved unchanged) to maintain high-quality candidates. Over multiple generations, the GA's population tends to evolve toward an optimum, though it may not guarantee a global solution [82]. Nonetheless, GAs remain popular in

electric machine design optimization, with several applications specifically targeting IPM motors [81].

The design of electric traction motors inherently involves trade-offs among multiple conflicting objectives, such as electromagnetic efficiency, torque density, rare-earth material usage, and cost. Multi-objective optimization (MOO) techniques are well suited to address these trade-offs, as they allow the generation of Pareto-optimal solutions that reflect the full set of possible compromises.

Among various MOO approaches, Multi-Objective Genetic Algorithms (MO-GAs) have gained wide adoption due to their robustness, flexibility, and effectiveness in exploring non-convex solution spaces without requiring gradient information. MO-GAs operate by generating a population of solutions, applying selection, crossover, and mutation operators to evolve toward the Pareto front. Once the front is obtained, the designer can select the preferred compromise among the different goals with a clear view of how much each objective is penalized by the improvement of another one [83].

Multi-objective electric motor design methodologies are strongly supported by recent literature. Sardar et al. [84] presents a comprehensive overview of optimization strategies for the design of Interior IPMSMs, categorizing them into gradient-based methods, surrogate-model approaches, and nature-inspired algorithms. Among the latter, Multi-Objective Evolutionary Algorithms (MOEAs) such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), and particularly Particle Swarm Optimization (PSO) and its advanced variants (Speed-constrained Multi-Objective PSO (SMPSO), Optimized Multi-Objective PSO (OMOPSO), and Modified PSO (MPSO)) are identified as among the most widely adopted methods for electric traction motor design, owing to their capacity to efficiently explore high-dimensional, non-convex, and multi-constrained design spaces.

The case study included a PSO-based multi-objective optimization framework aimed at minimizing torque ripple, magnet volume, and electromagnetic losses, while simultaneously maximizing torque and operational efficiency [85].

[86] proposed a framework that incorporates robustness verification by performing a statistical sensitivity analysis using Latin Hypercube Sampling (LHS), enabling the identification of parameter variations that most significantly affect key performance indicators, and ensuring that the optimized IPMSM design main-

tains acceptable performance across a wide range of operating and manufacturing uncertainties.

Additionally, Ma et al. [87] applied a MOGA to the design of an IPM motor with combined radial and tangential flux paths, optimizing geometric parameters to enhance partial-load efficiency and magnetic performance under driving cycle constraints. Their work validates the role of MOGA in handling unconventional topologies and integrated objectives.

In contrast with evolutionary-based methods like MOGA, Barri et al. [88] propose a supervised-learning-assisted optimisation approach leveraging an Adaptive Pareto Algorithm (APA). This method employs artificial neural networks as surrogate models and introduces a three-stage iterative process: design space reduction, local infill, and uniformisation, to efficiently converge toward an evenly distributed Pareto front.

Driving cycle–based optimization. Traditionally, IPM design methodologies focus on a rated operating point (peak torque or base speed). However, BEVs usage spans a wide torque speed envelope. Incorporating full drive cycles (WLTC, NEDC, or real data) in the design method evaluation ensures the “best-efficiency zone” aligns with actual usage [29, 89]. [90] shows that shaping flux barriers for urban duty cycles (repeated accelerations, high copper losses) can differ significantly from shapes optimized for sustained high-speed operation.

To accelerate the optimization routine, an option is to select a limited number of equivalent operating points for EM analysis and evaluation. The concepts of “geometrical center of gravity” and “energy center of gravity” have been introduced for selecting representative operating points from a given driving cycle [81].

Thermal and multi-physics considerations. High power densities in IPMs require rigorous thermal modeling (lumped-parameter or 3D fluid–thermal analysis) to keep magnets and windings under safe temperature limits. Mechanical checks ensure rotor integrity at high speeds and repeated load cycles [75]. Modern frameworks thus embed electromagnetic, thermal, and mechanical simulation within an optimization loop. Mechanical analysis are particularly impacting in high-speed applications, where the rotor is subjected to high centrifugal stresses. Surrogate models can mitigate the computational burden [88]. Coupling electromagnetic simulations with these multi-physics aspects ensures the final IPM design is robust to extended driving cycles and peak power demands [91].

By merging these trends, the objective is to develop a comprehensive optimal design methodology based on MOGA, leveraging multiple driving cycles, and multi-physics analysis, aimed at optimizing an innovative electric drive module for reconfigurable, low-voltage battery electric vehicle applications.

2.3 Drive system modeling

The proposed battery electric vehicle with its traction system has been modeled using a multi-step approach. First, a backward model is developed to determine the target operating points for the two vehicle configurations; these targets serve as essential inputs for the electric motor design process. The electromagnetic model of the electric motor, developed in Ansys MotorCAD [92], is presented alongside its mechanical and thermal models. Finally, a complete forward vehicle model is developed and validated, and it is employed to assess the system performance at the vehicle level, including efficiency and driving range.

2.3.1 Vehicle backward modeling and target points definition

A backward vehicle model is employed to calculate the torque-speed envelope required to follow a prescribed speed profile. In this approach, the desired vehicle speed is imposed as input, and the simulator determines the net tractive force required, accounting for payload, road gradient, and vehicle parameters. From this, the operating conditions of the electric motor and its energy consumption can be computed by evaluating the corresponding torque and speed demands, considering the characteristics of the vehicle.

The analyzed reconfigurable vehicle is a fully electric, front-wheel-drive passenger car equipped with a single electric motor coupled to a fixed-gear transmission. Together with the inverter, these components constitute the Electric Drive Module. The main parameters of the two configurations of the Low Voltage Reconfigurable Electric Vehicle are reported in Table 2.2.

The vehicle longitudinal dynamic is modeled as a two-axle rigid body, considering all driving resistances. Assuming the total mass is concentrated at the vehicle's center of gravity (CoG), the equilibrium of forces governs the vehicle's acceleration,

Table 2.2 Low Voltage Reconfigurable Vehicle parameters

Parameter	Symbol	Frugal	Dual
Mass (curb weight)	$M_{\text{veh,curb}}$	900 [kg]	1000 [kg]
Mass (GVW)	$M_{\text{veh,GVW}}$	1250 [kg]	1350 [kg]
WLTP test mass	$M_{\text{veh,WLTP}}$	1052 [kg]	1152 [kg]
Wheelbase	l	2.32 [m]	2.32 [m]
Rolling resistance coefficient	f_r	5.3 [N/kN]	5.3 [N/kN]
Wheel radius	R_w	0.30 [m]	0.30 [m]
Drag coefficient	C_d	0.33 [-]	0.33 [-]
Frontal area	A_f	2.15 [m ²]	2.15 [m ²]
Gearbox efficiency	η_{gb}	0.97 [-]	0.97 [-]

expressed as:

$$M_{\text{veh}} \frac{dv}{dt} = F_{\text{trac}} - F_{\text{aero}} - F_{\text{roll}} - F_{\text{grade}}. \quad (2.1)$$

The aerodynamic drag force is defined as:

$$F_{\text{aero}} = \frac{1}{2} \rho_{\text{air}} A_f C_d v^2, \quad (2.2)$$

where ρ_{air} is the air density, A_f is the frontal area, C_d the drag coefficient, and v the vehicle speed.

Rolling resistance, due to tire deformation losses, is modeled as:

$$F_{\text{roll}} = f_r F_z, \quad (2.3)$$

where f_r is the rolling resistance coefficient, assumed constant in this study, and F_z is the vertical load on the tires. As analyzed in previous works [93], f_r can vary with speed, tire pressure, and longitudinal slip. The adopted value represents the average coefficient across a complete driving cycle, based on data provided by the tire manufacturer.

On inclined roads, the gravitational component is expressed as:

$$F_{\text{grade}} = M_{\text{veh}} g \sin(\alpha), \quad (2.4)$$

where g is the gravitational acceleration and α is the road gradient.

The torque at the wheels T_{axle} is calculated as:

$$T_{\text{axle}} = F_{\text{trac}} \cdot R_w. \quad (2.5)$$

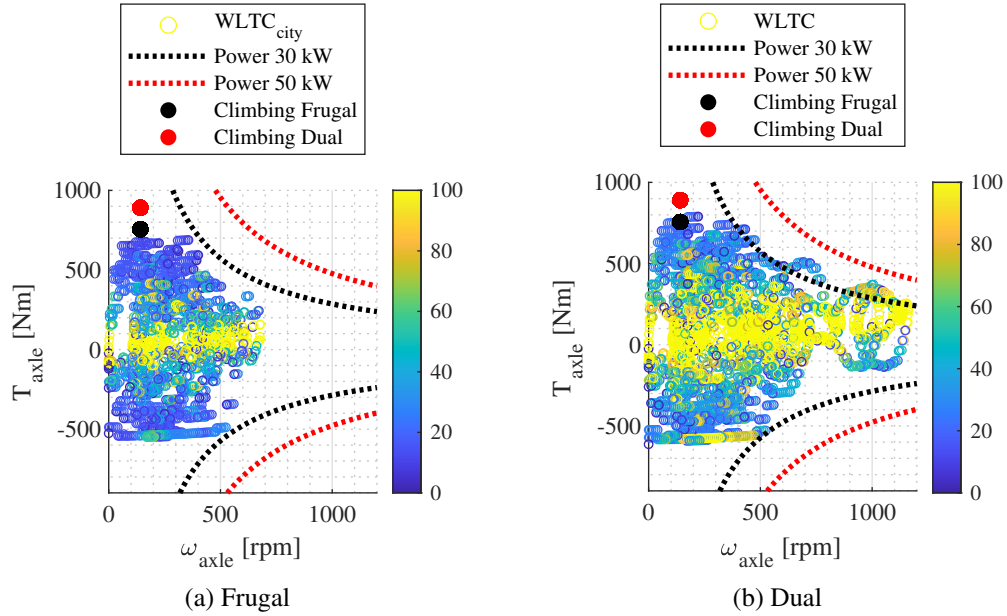


Fig. 2.2 Working points at the wheels as torque and rotational speed, from backward simulation.

Figure 2.2 illustrates the required operating points at the wheels in terms of torque and rotational speed for both the Frugal and Dual configurations, in traction and braking conditions. In the Frugal configuration, conceived for urban driving, only the urban section of the WLTC driving cycle ($WLTC_{\text{city}}$) is considered. In contrast, the Dual configuration is designed to fulfill the complete WLTC Class 3 cycle [94]. In these simulations, the WLTP test mass is considered. The color bar indicates the occurrence of the working points during the driving cycle. As it emerges from the figures, in the Frugal mode a power of 30 kW is needed to complete the urban driving cycle; while in the Frugal mode, a power of 50 kW is needed to fulfill the complete cycle.

Additionally, the operating envelope includes climbing mission requirements defined in Table 2.1. These climbing points are fundamental for determining the minimum torque requirement ($\approx 750 - 850$ Nm, for Frugal and Dual mode), while the vehicle's maximum speed is set according to the peak speed reached during the driving cycle.

The torque and speed demands at the wheels are converted to the electric motor level by applying a fixed gear ratio τ_{gb} , and a constant gearbox efficiency η_{gb} . This mapping allows the translation of vehicle-level performance requirements into the electric motor design space, ensuring that the EDM is capable of meeting all mission profiles and that its design is optimized accordingly.

2.3.2 Electromagnetic modeling of the IPM

In this work, the electromagnetic behavior of the interior permanent magnet machine is analyzed under a magnetostatic finite element method, where each operating point is solved independently with constant stator currents (fixed magnitude and angle). This approach is implemented in the software Ansys MotorCAD [92], which automates mesh generation, boundary condition handling, and post-processing for a wide range of steady-state operating conditions [95].

From a theoretical standpoint, the relevant Maxwell equations for the magnetostatic case are:

$$\nabla \times \mathbf{H} = \mathbf{J} \quad (2.6)$$

$$\nabla \cdot \mathbf{B} = 0, \quad (2.7)$$

$$\mathbf{B} = \mu(\mathbf{H}) \mathbf{H}, \quad (2.8)$$

where $\mathbf{H}$ is the magnetic field intensity, $\mathbf{J}$ is the current density in the stator windings, $\mathbf{B}$ is the magnetic flux density, and $\mu(\mathbf{H})$ captures any nonlinear permeability to account for saturation in the lamination steel. Because each operating point is time-invariant, parasitic eddy currents in the rotor or magnets are not explicitly computed. This significantly reduces the computational effort, making it practical to evaluate large numbers of points in the torque–speed space.

After obtaining the magnetostatic solution (i.e., local $\mathbf{B}$ field) at each operating point, the machine's losses and efficiency are evaluated.

The machine's electromagnetic torque maps can be derived as a function of rotational speed ω by leveraging both the maximum torque per ampere (MTPA) and maximum torque per volt (MTPV) strategies [96]. For this purpose, a synchronous rotating dq -axis framework is applied in the steady state, so that the governing

voltage and torque equations become:

$$v_d = R i_d - p \omega_m \lambda_q(i_d, i_q), \quad v_q = R i_q + p \omega_m \lambda_d(i_d, i_q), \quad (2.9)$$

$$T_m = \frac{3}{2} p \left[\lambda_d(i_d, i_q) i_q - \lambda_q(i_d, i_q) i_d \right], \quad (2.10)$$

where the subscripts d and q denote the machine axes for voltages v , currents i , and flux linkages λ . The flux linkage maps λ_d and λ_q are extracted via finite element analysis, taking into account any saturation.

Multiple loss components, including winding (both DC and AC), iron (core), and magnet losses, are considered when generating the efficiency map. The DC winding (copper) losses follow the Joule loss expression

$$P_{dc} = 3 R_{ph} I_{ph}^2, \quad (2.11)$$

where R_{ph} is the phase resistance, and I_{ph} is the RMS phase current. Meanwhile, AC winding losses are modeled in Ansys Motor-CAD [92] to account for frequency-dependent skin and proximity effects.

Iron (core) losses in the stator and rotor laminations are evaluated through a Bertotti-based method [97], yielding:

$$P_{iron}^* = k_h f B^{3.701} + k_{eddy} f^2 B^2 + k_{exc} f^{1.5} B^{1.5} \quad [\text{W/kg}], \quad (2.12)$$

where k_h, k_{eddy}, k_{exc} are the respective coefficients for hysteresis, eddy currents, and excess losses referred to the NO20 electrical steel, f is the electrical frequency, and B is the local flux density.

Magnet volume losses are evaluated from the induced eddy-current density J_e , which depends on $\partial \mathbf{A} / \partial t$, the time variation of the magnetic vector potential:

$$P_{pm}^* = \sigma_{pm} \left(\frac{\partial \mathbf{A}}{\partial t} \right)^2 \left[\frac{\text{W}}{\text{m}^3} \right], \quad (2.13)$$

where σ_{pm} is the magnet's electrical conductivity. This expression is constrained to ensure that the net current in each magnet remains zero at any instant.

Finally, the machine's efficiency in motoring mode is given by the ratio of mechanical power to the total input power:

$$\eta_m = \frac{T_m \omega_m}{T_m \omega_m + P_w + P_{\text{iron}} + P_{\text{pm}}}, \quad (2.14)$$

where T_m is the electromagnetic torque from (2.10), ω_m is the mechanical speed, P_w represents winding losses, P_{iron} is integrated from (2.12) over the machine's laminated volumes, and P_{pm} denotes any magnet conduction losses via (2.13).

Collectively, (2.9)–(2.14) represents the basis for constructing the torque, flux linkage, and loss maps. By systematically stepping through multiple current vectors and speeds, the full efficiency map can be obtained, which is essential for drive-cycle-based analyses and design optimization tasks. The magnetostatic approach therefore strikes a balance between computational efficiency and the physical fidelity required to guide engineering decisions for the IPM traction drives.

2.4 Electric drive module design

The design of the electric drive, aimed at fulfilling the vehicle-level requirements defined in Table 2.1 and Figure 2.2 through backward vehicle simulation, begins with a set of initial design choices regarding the motor topology and basic dimensions. These fundamental decisions are primarily guided by the need to integrate the new drive within the original packaging constraints of the donor vehicle, a Fiat 500e. A first IPM baseline solution FEA model is developed to set the hairpin winding topology and the gear set basic layout and ratio. The winding pattern is refined with the hairpin manufacturer, to set proper stator design space and constraints. With these parameters, the point clouds of the required EM working points for the reference driving missions are obtained.

Once these baseline design choices are defined, along with the design space boundaries and system constraints, a Multi-Objective Genetic Algorithm is applied to optimize the details of the electric motor's efficiency, by varying the section geometry parameters. This optimization is performed considering the complete driving cycle working points of the two vehicle configurations while ensuring compliance with the performance requirements of the defined driving missions. The choice of a Multi-Objective Genetic Algorithm among various genetic algorithm options is

motivated by the need to optimize the design across multiple driving missions, in alignment with the reconfigurable nature of the proposed vehicle. This approach allows prioritization of specific driving scenarios during the optimization process, thus ensuring the design is tailored to diverse usage profiles. The flowchart of the overall design methodology is in Figure 2.3.

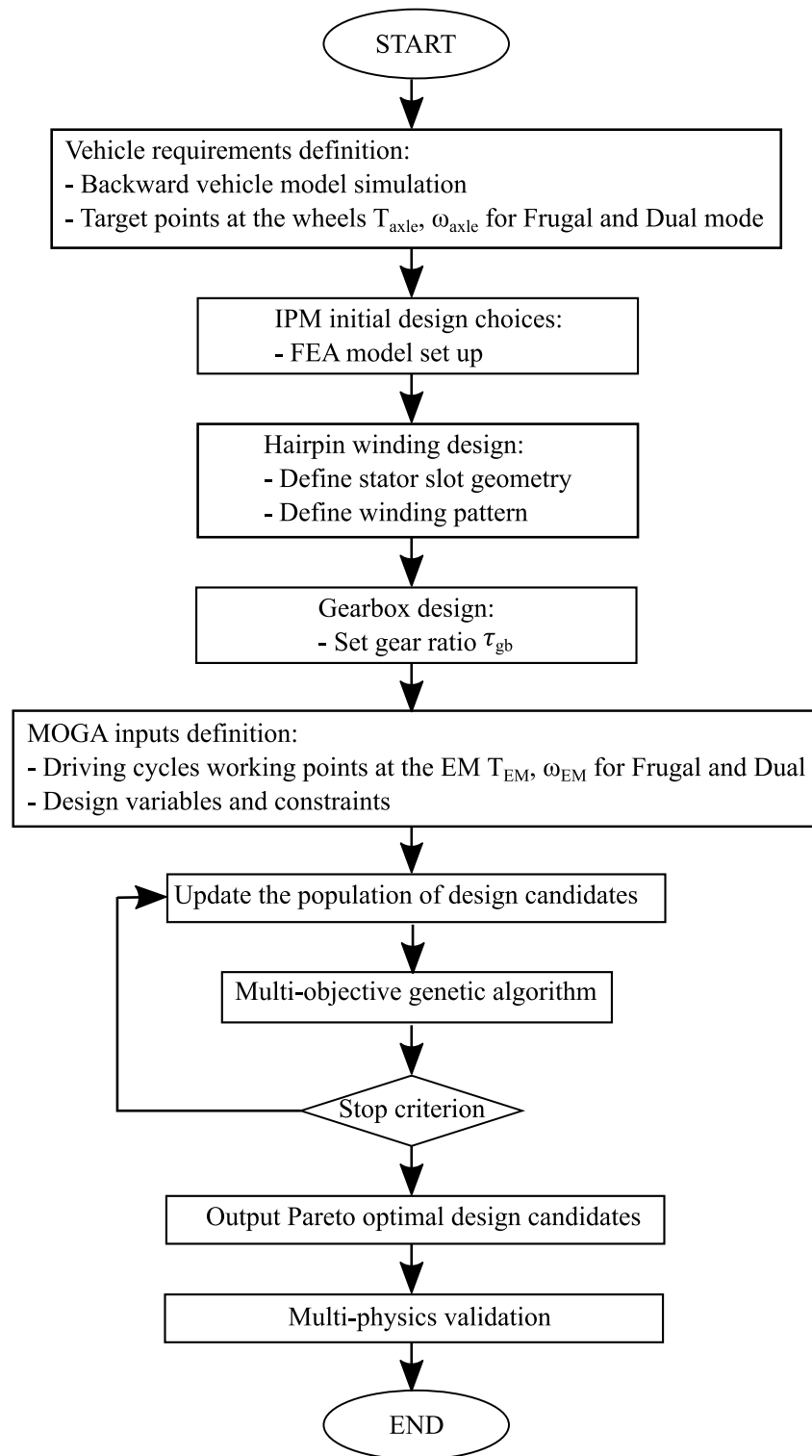


Fig. 2.3 Flowchart of the overall design methodology.

2.4.1 Initial design choices

The selected electric drive is a 48 V Interior Permanent Magnet Synchronous Motor (IPMSM), featuring a single-layer V-shaped rotor topology with NdFeB N42SH magnets, four pole pairs, and a 48-slot stator. The full-pitch distributed six-phase hairpin winding design is described in detail in Section 2.4.2, while the main drive specifications are summarized in Table 2.3. The Electric Drive Module (EDM) includes a single-speed, two-stage reducer; however, the gear ratio selection is not included in the MOGA optimization process, as discussed in Section 2.4.3. Additionally, the motor is equipped with a water-cooling system via a cooling jacket, ensuring optimal operating temperatures under varying load conditions.

Table 2.3 Motor drive main specifications

Specification	Symbol	Value
Stator slots	N_s	48
Pole pairs	p	4
DC link voltage	V_{dc}	48 [V]
Peak line current (10 s)	$I_{rms,peak}$	450 [A]
Continuous line current	$I_{rms,cont}$	250 [A]
Magnets	—	N42SH
Lamination material	—	NO20
Stack length	l_s	105 [mm]
Maximum stator external diameter	$d_{so,max}$	178 [mm]
Maximum speed	ω_{max}	14000 [rpm]
Cooling system	—	Water jacket (spiral)
Gear ratio (single speed)	τ_{gb}	10.2

Regarding the stator design, the adoption of 48 slots with a distributed winding configuration aligns with current trends in automotive traction motors, which prioritize high torque smoothness and reduced harmonic content. Distributed windings, particularly with a higher number of slots, enable better space utilization, lower copper losses, and reduced torque ripple and electromagnetic noise, ultimately enhancing efficiency and drivability in electric vehicle applications [98].

The selection of NdFeB N42SH magnets for the IPM design is driven by the demanding requirements of electric traction applications, where high torque density, thermal stability, and resistance to demagnetization are critical within commercially available magnet solutions. The N42SH grade, in particular, provides an optimal

trade-off between magnetic performance and thermal robustness, with a maximum operating temperature of 150°C and elevated intrinsic coercivity, ensuring protection against irreversible demagnetization during high-speed field-weakening operation [90]. From Figure 2.4, it emerges that for temperatures below 120°C, the permanent demagnetization point (B_{knee}) occurs at a value lower than 0 T, while the magnetic flux density in the magnets under short-circuit conditions is $B_{mag} = 0.56$ T.

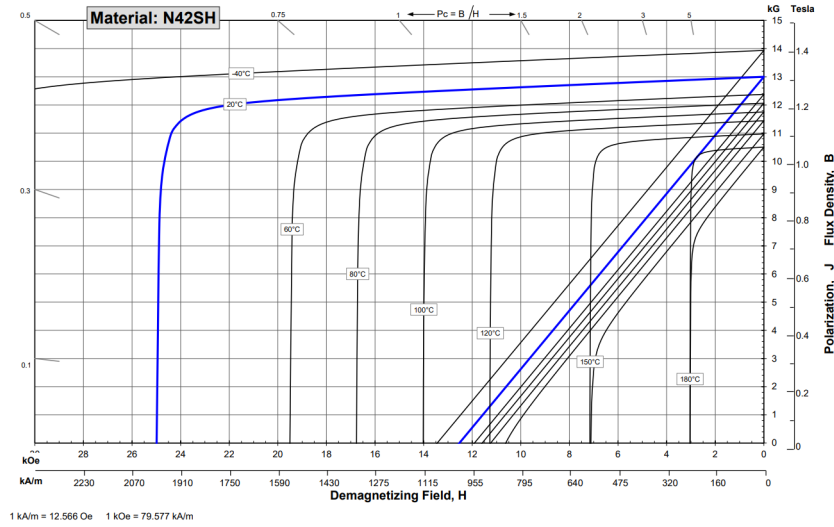


Fig. 2.4 Magnetization curve $B-H$ of the selected permanent magnet material NdFeB N42SH, illustrating the relationship between magnetic flux density B and magnetic field strength H at different temperature level.

The V-shaped rotor topology is chosen for its well-documented advantages in traction applications, where a combination of high torque density, effective flux weakening, and mechanical robustness is essential. The V-shape configuration aligns the permanent magnets along the q-axis flux lines, maximizing torque production while improving flux-weakening performance at high speeds. This design choice is widely adopted in automotive IPMs, as it offers a balance between performance and manufacturability [29].

The machine features four pole pairs (8 poles), a common choice in traction motors that provides a balance between torque production, efficiency, and mechanical constraints.

The maximum operating speed is set to 14000 rpm, corresponding to the maximum vehicle speed in Dual mode, as defined in Table 2.1 and Figure 2.2, considering the selected gear ratio. The values of maximum peak current ($I_{rms,peak}$) and contin-

uous current ($I_{\text{rms,cont}}$) are set according to the inverter manufacturer's limitations, leading to a maximum continuous current density of $J_{\text{cont}} = 8 \text{ A/mm}^2$ and a peak current density of $J_{\text{peak}} = 14 \text{ A/mm}^2$.

The active length of the stator and rotor stack is set $l_s = 105 \text{ mm}$, consistently with the mechanical position of the ball bearings on the original drive case.

The parametrized cross-section of the IPM, along with the key design parameters, is shown in Figure 2.5. The design variables include both stator and rotor parameters.

The stator parameters are:

- Outer radius: r_{so}
- Inner radius: r_{si}
- Slot depth: d_s
- Slot opening width: w_{so}
- Tooth width: w_t

The rotor parameters are:

- Outer radius: r_{ro}
- Web width: w_w
- Permanent magnet angle: α_{pm}
- Magnet width: w_{pm}
- Magnet thickness: h_{pm}
- Bridge thickness: w_b

As reported in Table 2.5, these parameters serve as design variables for the optimization algorithm. Some of these variables are set: the air gap is fixed at $h_g = 0.7 \text{ mm}$, while the rotor inner radius is set to $r_{\text{si}} = 65 \text{ mm}$, consistent with the drive shaft diameter.

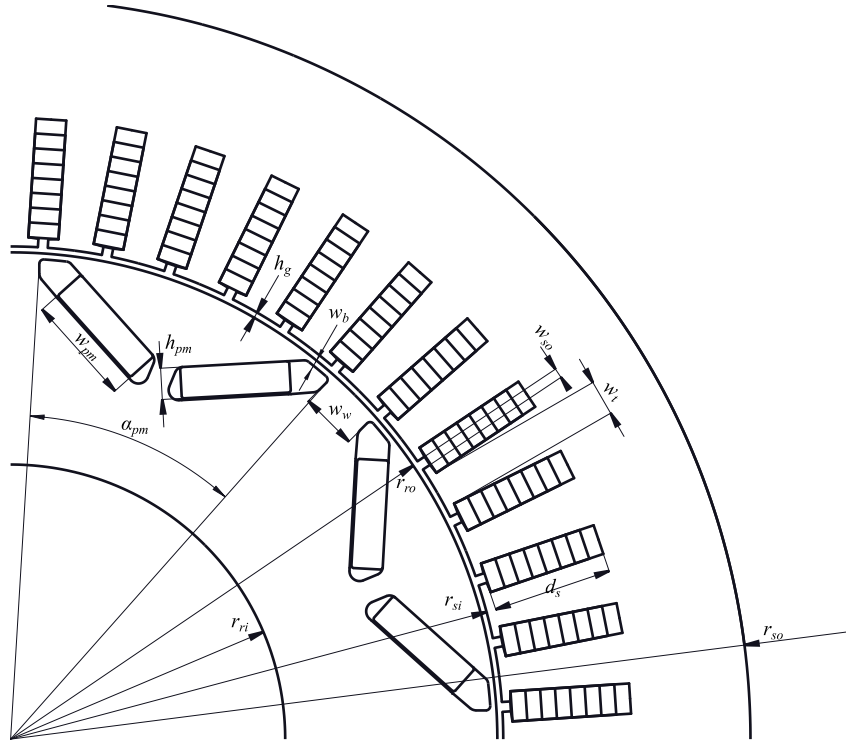


Fig. 2.5 Cross section of the studied IPM, comprising the design parameters.

2.4.2 Winding topology

The winding topology is defined prior to the MOGA optimization routine to ensure that the EM geometry is optimized including the proper winding pattern. This also allows for the stator characteristics (slot dimensions) to be fixed in compliance with hairpin winding manufacturing constraints while acknowledging the central role of the winding design in the overall functionality of the vehicle architecture.

The decision to utilize a multiphase winding scheme is crucial for the low voltage and reconfigurable characteristics of the LVREV EDM, and it is motivated by several beneficial attributes [99];

- Reduced power/current requirement for each phase.
- Capability for fault-tolerant operation.
- Enhanced torque density.

- Improved magnetomotive force distribution, and decreased DC-Link current ripples.
- Improved voltage handling capabilities: The use of dual inverters, each managing a portion of the motor phases, splits the current into more phases, thus increasing the system power at an identical voltage level. This effect facilitates higher operational speeds, enhances the magnetic field strength, and more efficiently counters back electromotive force (back-EMF).

The enhanced voltage handling capability of multi-phase electric machines makes this solution particularly effective for the low-voltage LVREV application [74]. Furthermore, emerging power electronics solutions based on GaN technology offer improved commutation performance and efficiency. However, these devices require lower phase currents, making multi-phase configurations a fundamental choice to fully leverage their advantages [100].

A hairpin winding is a type of stator winding configuration that utilizes rectangular cross-section conductors, which are pre-formed, inserted into the stator slots, and subsequently welded to create the desired coil connections. This design allows for a greater number of parallel branches, effectively reducing the per-branch current while maintaining the required overall current level. This technology, compared to standard stranded wire ones, can achieve a high fill factor and good thermal performance, making them a suitable choice for low-voltage, high-current electric drives, where efficient current handling and optimal slot utilization are essential for maximizing performance and efficiency [101].

Within this framework, the proposed IPM features a six-phase hairpin full-pitch winding pattern. Specifically, the six-phase machine adopts an asymmetrical winding configuration, with a spatial phase displacement of 30° between the two three-phase windings. The two neutral points remain isolated, preventing the circulation of zero-sequence currents, which enhances DC link utilization, simplifies current control, and allows fail-safe operations in the case only one inverter is powered.

Figure 2.6b illustrates the winding pattern of the six-phase EDM, while Figure 2.6a presents a comparative depiction of the same motor configured with a three-phase arrangement. The radial view of the phase 1 arrangement is reported in Figure 2.7a.

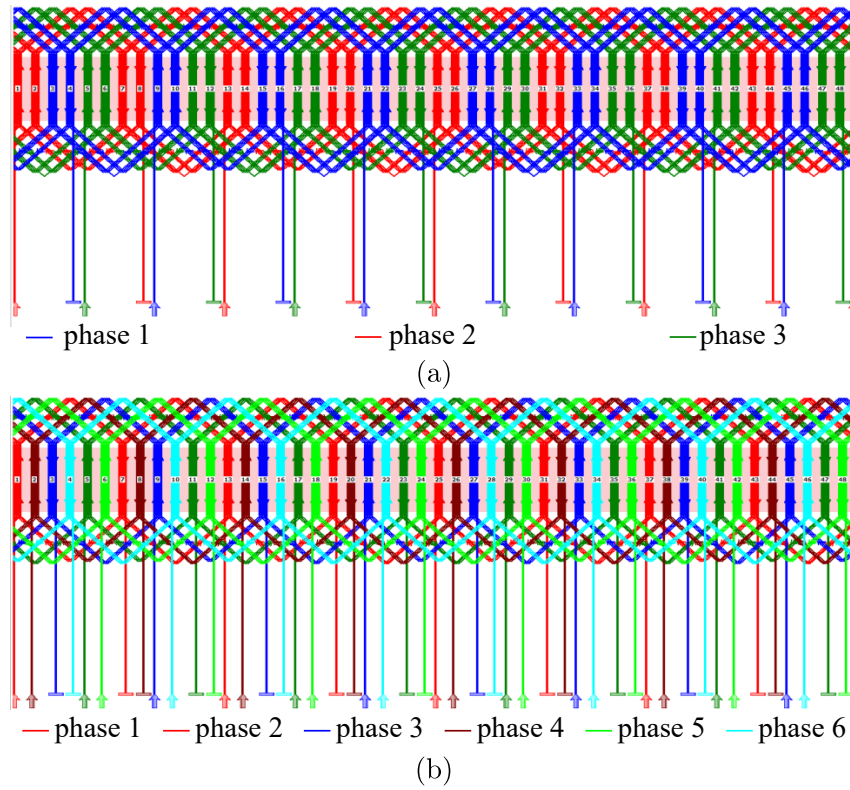


Fig. 2.6 Linear winding pattern for (a) three-phase and (b) six-phase.

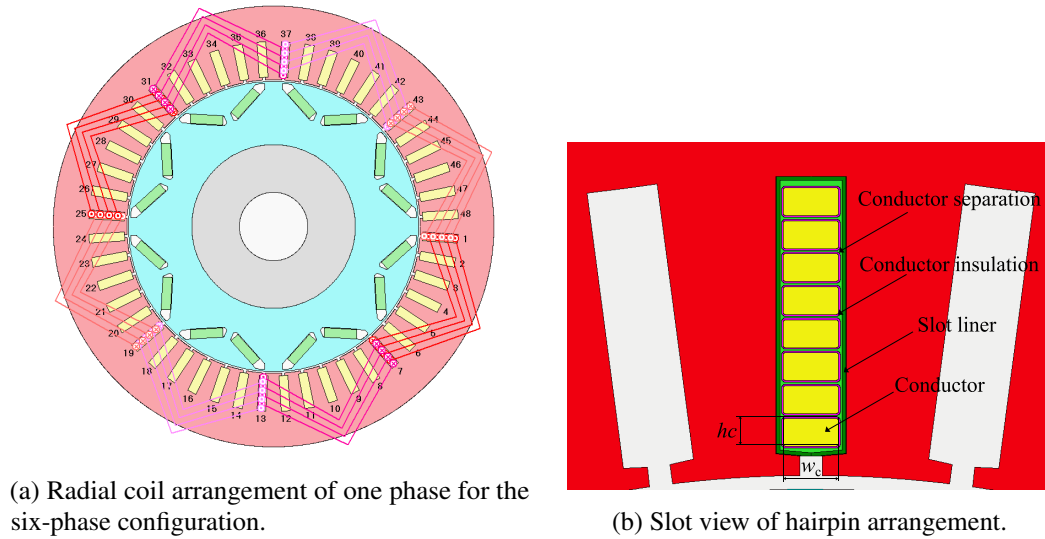


Fig. 2.7 Hairpin winding details

The specifications of the LVREV hairpin winding are summarized in Table 2.4. A preliminary FEA model of the IPM is developed to define and assess the main

features of the proposed winding topology. The following sensitivity analyses are performed on a baseline EM solution featuring the specifications of Table 2.3.

Table 2.4 Hairpin winding specifications

Specification	Symbol	Value
Phase distribution		$N \times 3$ phase (asymmetric, 30° shift)
Phase number	N_p	6
Parallel paths	N_{pp}	8
Winding layers, per slot	N_{ws}	8
Conductor width	w_c	2.8 [mm]
Conductor height	h_c	1.4 [mm]
Insulation thickness	t_i	0.1 [mm]
Liner thickness	t_l	0.19 [mm]
Wire slot fill factor	k_f	0.84
Slot depth	d_s	15.17 [mm]
Slot width	w_s	3.58 [mm]

In low-voltage applications, operating at high currents and high frequencies necessitates the use of multiple parallel paths in the winding design. This approach reduces the conductor cross-section, and ensures compliance with the voltage constraints. However, to prevent current imbalance and additional copper losses, it is essential to equalize the impedance of each parallel path. This requires the proper arrangement of the hairpin so that each parallel path has the same electrical characteristics. Specifically, the following design rules must be satisfied: [102]

- The number of winding layers must be even.
- Conductors belonging to the same parallel path must span all slot layers to ensure equal inductance per path.
- Conductors of the same parallel path must be distributed across all slots per pole of that phase to guarantee identical induced EMF.

The design rules are converted in analytical expressions:

$$\frac{\text{number of conductors per parallel path}}{\text{number of winding layers}} = \frac{N_s N_{ws}}{N_p N_{pp}} = \text{integer} \quad (2.15)$$

$$\frac{\text{number of conductors per parallel path}}{\text{number of slots per pole per phase}} = \frac{2pN_{ws}}{N_{pp}} = \text{integer} \quad (2.16)$$

The selection of eight parallel paths is motivated by analyzing the induced peak line-to-line back-EMF (Figure 2.8), $E_{b,\text{peak}}$, at the base speed of 4500 rpm. For a single parallel path, the computed $E_{b,\text{peak}}$ is approximately 195 V, which is incompatible with the 48 V DC-link voltage, as it results in a voltage ratio $195/48 > 4$. According to the design constraints, the first feasible value beyond 4 is 8, which yields $E_{b,\text{peak}} < 40$ V, making it compliant with the system voltage limitations. This configuration ensures the possibility of using conductors with the cross-sectional area reported in Table 2.4 (approximately 4 mm²), maintaining a current density of about 14 A/mm² (thermal constraint) and achieving the phase current of 450 A compliant with power electronics specifications.

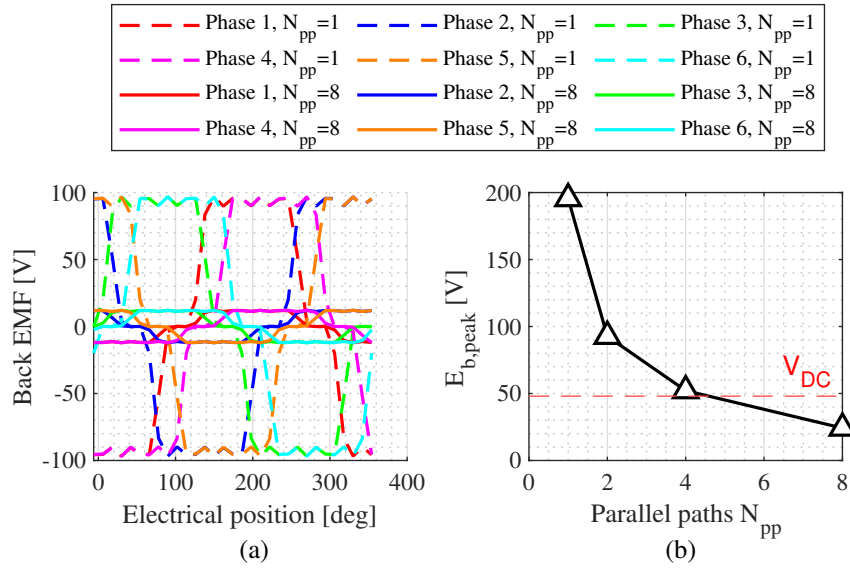


Fig. 2.8 Induced back EMF at 4500 rpm. Comparison between the cases with 1 and 8 parallel paths winding arrangement. Sensitivity analysis of the line-to-line peak Back EMF $E_{b,\text{peak}}$ with feasible parallel path arrangements

Figure 2.9 evaluates the influence of the number of winding layers on the slot fill factor and power losses at both low and high speeds. In this sensitivity analysis, AC losses are computed using a full FEA method. Generally, increasing the number of winding layers in a hairpin winding reduces AC copper losses [103]. However, this typically results in higher DC copper losses due to the reduction of the fill factor, as

additional insulation layers are required between winding layers, as shown in Figure 2.9a.

In this study, AC and DC losses are analyzed for the considered machine with different winding layer configurations (2, 4, 6, and 8). Figures 2.9c and 2.9d illustrate the variations in AC and DC copper losses as the number of layers increases, at two operating speeds: low speed (1000 rpm) and high speed (12000 rpm). At 1000 rpm, DC copper losses dominate and remain nearly constant as the number of layers increases. At 12000 rpm, however, AC copper losses become the dominant component and decrease significantly with an increasing number of winding layers, whereas DC copper losses slightly increase due to the higher winding resistance.

Considering the total losses, the results indicate that increasing the number of layers leads to an overall reduction in total losses under high-speed conditions. There is not a loss reduction between 6 and 8 layers; however, the selected solution is 8 layers, as a 6-layer configuration would result in a line current exceeding 500 A (Figure 2.9b), which is unfeasible given the inverter's current constraint of $I_{\text{rms,cont,max}} = 450$ A.

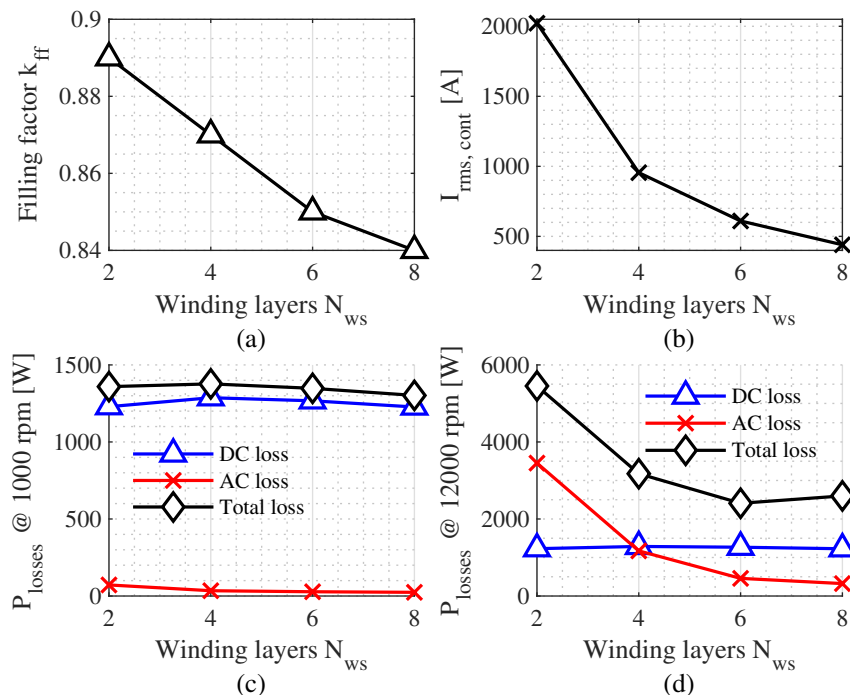


Fig. 2.9 Impact of winding layers per slot on: (a) slot fill factor; (b) line current; (c) power losses at 1000 rpm; (d) power losses at 12000 rpm.

2.4.3 Gearbox considerations

The proposed EDM interfaced with the original interfaces and casing of the Fiat 500e, thus the basic gearbox configuration is preserved. The reducer unit features a two-stage gear reduction system. The input shaft, supported by two deep groove ball bearings, drives the first stage pinion. The intermediate shaft, equipped with a gear and a pinion, transmits power to the second stage. The differential, mounted on tapered roller bearings, distributes torque based on the rotational speed of the half-shafts. Due to manufacturing constraints, only the second stage of the gears can be modified to achieve the target gear ratio.

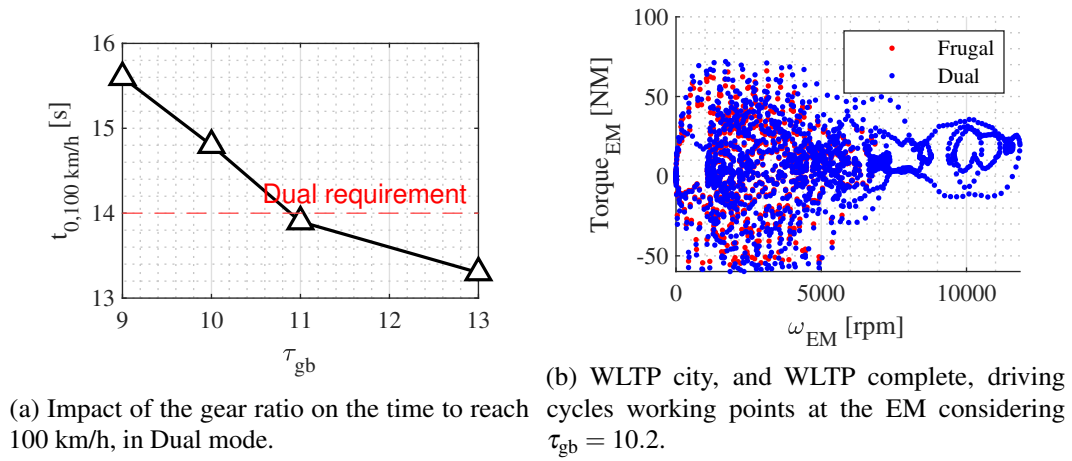


Fig. 2.10 Gear ratio selection.

The baseline IPM is integrated into a vehicle model to evaluate acceleration performance across different gear ratios. The gear ratio is varied between 9 and 13, considering manufacturability constraints. The acceleration time to reach 0–100 km/h $t_{0-100 \text{ km/h}}$ in Dual mode is used as a key performance indicator. As illustrated in Figure 2.10a, the requirement of 14 s (Table 2.1) is met with $\tau_{gb} \simeq 11$. However, considering modifications limited to the second gear stage, the selected gear ratio is $\tau_{gb} = 10.2$. The subsequent optimization of the electric machine is expected to further enhance performance.

The current two-stage architecture, starting from the production Fiat 500e gearbox with a total gear ratio of:

$$\tau_{\text{original}} = \frac{77}{29} \cdot \frac{72}{20} = 9.58$$

was modified by increasing the second stage, yielding:

$$\tau_{\text{mod}} = \frac{77}{29} \cdot \frac{73}{19} = 10.2$$

The module of the helical gear set is $m_n = 2.65$ mm, with a helix angle $\beta = 30^\circ$, resulting in a transverse module:

$$m_t = \frac{m_n}{\cos \beta} \approx 3.06 \text{ mm}$$

Further increasing τ beyond 10.2 would require either increasing the driven gear teeth number or reducing the pinion below 29 teeth, which would lead to a lower gear module (e.g., $m_n < 2.5$ mm). This would result in thinner teeth, lower bending strength, and reduced fatigue life, as well as manufacturing challenges. Therefore, the selected ratio of 10.2 ensures a good compromise between torque amplification and gear robustness.

Figure 2.10b depicts the driving cycle working points of the electric machine for both Frugal and Dual modes, considering WLTP city and WLTP complete for the two vehicle configurations, which serve as inputs for the Multi-Objective Genetic Algorithm.

2.4.4 Multi-objective genetic algorithm

The IPM geometry cross section is optimized with a multiple-driving cycle-based Multi-objective genetic algorithm (MOGA). The main steps of the proposed algorithm are summarised in Figure 2.11.

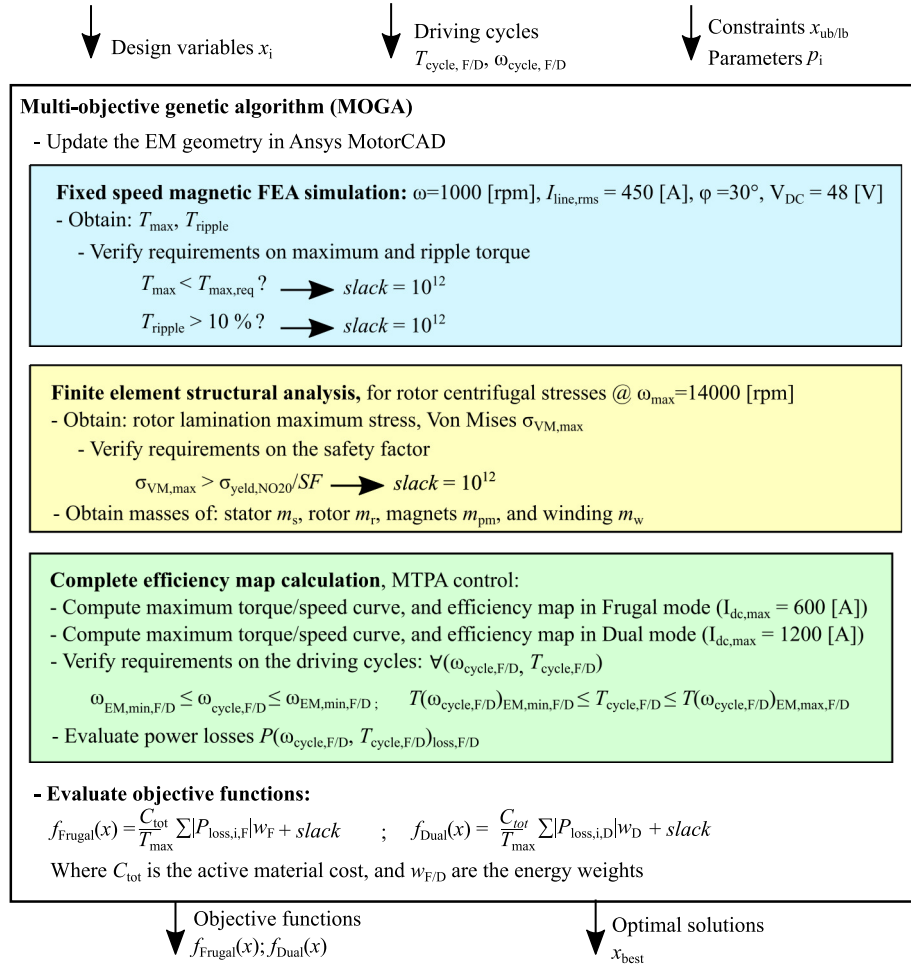


Fig. 2.11 Multi-objective genetic algorithm for EM design block scheme.

The MOGA is implemented using the "gamultiobj" function in MATLAB. This function is designed for solving multi-objective optimization problems by evolving a population of candidate solutions across multiple generations while maintaining a diverse set of Pareto-optimal solutions. The algorithm is structured with a population size of 18, ensuring a manageable yet effective exploration of the design space.

The initial population is selected from a precomputed random baseline dataset. The best-performing individuals are extracted and used as the starting point for the genetic algorithm, enhancing convergence efficiency. The Pareto fraction is set to 0.7, meaning that 70% of the population is retained for non-dominated sorting at each generation, balancing convergence and solution diversity.

The "gamultiobj" function employs a controlled elitist genetic algorithm (CNSGA-II), which uses crossover and mutation operators to generate new candidate solutions [104]. The maximum number of generations is set to 50, allowing sufficient evolution without excessive computational cost. The optimization process follows a stochastic evolution mechanism, using tournament selection to retain diversity and prevent premature convergence. The computation is executed in a sequential mode. The optimization is implemented in co-simulation between Matlab and Ansys MotorCAD.

The input to the MOGA function are:

- The design variables x_i , with the relative upper and lower bounds x_{ub} and x_{lb} , as reported in Table 2.5. The design variables are the main geometry characteristics of the IPM cross-section, including outer and inner radius of the stator, and the geometry of the rotor, for the selected topology. The slot dimensions are fixed according to the winding topology 2.4.2.
- The driving cycle working points $T_{cycle,F/D}$, $\omega_{cycle,F/D}$ at the EM for Frugal and Dual mode as depicted in Figure 2.10b.
- A set of fixed simulation parameters p_i .

Table 2.5 MOGA design variables

Design variable x_i	Description	Lower bound x_{lb}	Upper bound x_{ub}
r_{so}	Stator outer radius	167.4 [mm]	177.8 [mm]
r_{si}	Stator inner radius	110.0 [mm]	140.0 [mm]
w_{so}	Slot opening width	0.70 [mm]	2.50 [mm]
α_{pm}	PM V angle	20°	60°
h_{pm}	PM thickness	2.0 [mm]	5.0 [mm]
$\frac{w_{pm}}{w_{pm,max}}$	PM width, ratio	0.7	0.9
$\frac{w_w}{w_{w,max}}$	Web width, ratio	0.2	0.5
w_b	Bridge thickness	0.5 [mm]	1.0 [mm]

The first step consists of updating the EM geometry in MotorCAD with the design candidate. The process of evaluating the objective functions follows a multi-physics approach:

Fixed speed magnetic FEA simulation

The optimization process begins with a Finite Element Analysis (FEA) magnetic simulation at a fixed operating point to evaluate the electromagnetic performance of the machine setting the rotor speed to $\omega = 1000$ rpm, with an RMS phase current of $I_{\text{line,rms}} = 450$ A, a phase advance angle of $\varphi = 30^\circ$, and a DC-link voltage of $V_{\text{DC}} = 48$ V.

From this simulation, two critical performance indicators are extracted:

- Maximum torque (T_{max}): the peak electromagnetic torque that the motor can deliver under the given conditions.
- Torque ripple (T_{ripple}): the fluctuation in torque output caused by variations in the magnetic field distribution and cogging effects.

To ensure compliance with design constraints, the obtained values of T_{max} and T_{ripple} are verified against predefined limits:

$$T_{\text{max}} \geq T_{\text{max,req.}} \quad (2.17)$$

$$T_{\text{ripple}} \leq 10\% \quad (2.18)$$

where $T_{\text{max,req.}} = 80$ Nm is the torque needed to overcome the gradability requirement according to Table 2.1 and Figure 2.2, and 10% is the threshold limit for torque ripple to maintain smooth operation and minimize mechanical vibrations. If these constraints are violated, a large slack penalty of 10^{12} is assigned to discourage infeasible solutions in the optimization process.

Finite element structural analysis

The second step in the optimization workflow involves a finite element structural analysis to evaluate the mechanical integrity of the rotor under high-speed operation. This analysis is performed at a maximum rotational speed of $\omega_{\text{max}} = 14000$ rpm to ensure that the rotor can withstand the centrifugal forces generated at high speeds without exceeding material limits.

The key mechanical parameter extracted from this simulation is the maximum Von Mises stress ($\sigma_{\text{VM,max}}$) in the rotor lamination. This stress is compared against

the allowable yield strength of the rotor material $\sigma_{y,NO20}$, adjusted by a safety factor ($SF = 1.5$), to ensure structural reliability:

$$\sigma_{VM,max} \leq \frac{\sigma_{y,NO20}}{SF} \quad (2.19)$$

If the computed stress exceeds the allowable limit, a large slack penalty of 10^{12} is introduced to the objective function, preventing the selection of infeasible designs.

Additionally, this step provides the mass properties of the stator m_s , rotor m_r , permanent magnets m_{pm} , and hairpin winding m_w .

Complete efficiency map calculation and loss evaluation

The final step in the evaluation process involves the computation of the efficiency map using the LAB module in Ansys MotorCAD. This analysis aims to characterize the machine's performance across a wide range of operating conditions, considering both electromagnetic and thermal effects.

The efficiency map is generated by evaluating the electric machine's behavior under maximum torque per ampere (MTPA) control for two different operating conditions:

- Frugal mode: single battery module, discharge limit $I_{dc,max} = 600$ A.
- Dual mode: two battery modules, discharge limit $I_{dc,max} = 1200$ A.

For each mode, MotorCAD computes the maximum torque-speed envelope, determining the achievable operating region, and the efficiency map, considering stator copper losses, iron losses, permanent magnet eddy current losses, and mechanical losses.

The map is obtained by solving the machine model in 32 discrete operating points (ω_i, T_i) , uniformly distributed over the speed-torque plane. The results are then processed using a spline interpolation method to generate a continuous representation of the efficiency over the entire operating range.

To ensure the machine operates within the required limits imposed by the driving cycle, the obtained efficiency map is used to verify the following constraints:

$$\forall(\omega_{\text{cycle,F/D}}, T_{\text{cycle,F/D}}) \quad (2.20)$$

$$\omega_{\text{EM,min}} \leq \omega_{\text{cycle}} \leq \omega_{\text{EM,max}}, \quad (2.21)$$

$$T_{\text{EM,min,F/D}}(\omega_{\text{EM,cycle,F/D}}) \leq T_{\text{cycle,F/D}} \leq T_{\text{EM,max,F/D}}(\omega_{\text{EM,cycle,F/D}}) \quad (2.22)$$

where:

- $\omega_{\text{cycle,F/D}}, T_{\text{cycle,F/D}}$ are the operating points from the driving cycles, in frugal or dual mode.
- $\omega_{\text{EM,min}}, \omega_{\text{EM,max}}$ define the allowed speed range of the electric machine.
- $T_{\text{EM,min,F/D}}(\omega), T_{\text{EM,max,F/D}}(\omega)$ define the minimum and maximum torque available at each speed, in frugal or dual mode.

If a single point of the driving cycle is not included in the torque speed envelope of the relative configuration, a large slack penalty of 10^{12} is introduced to the objective function.

Finally, the power losses at each operating point are interpolated and evaluated:

$$P(\omega_{\text{cycle,F/D}}, T_{\text{cycle,F/D}})_{\text{loss}} \quad (2.23)$$

These losses are weighted based on the energy distribution across the driving cycle:

$$E_i = \frac{\omega_i T_i \pi}{30} \cdot \Delta t, \quad w_i^{\text{FD}} = \frac{E_i}{\sum_i E_i} \quad (2.24)$$

leading to the formulation of the final objective functions:

$$f_{\text{Frugal}}(x) = \frac{C_{\text{tot}}}{T_{\text{max}}} \sum_i P_{\text{loss},i}^{\text{F}} w_i^{\text{F}} + \text{slack} \quad (2.25)$$

$$f_{\text{Dual}}(x) = \frac{C_{\text{tot}}}{T_{\text{max}}} \sum_i P_{\text{loss},i}^{\text{D}} w_i^{\text{D}} + \text{slack} \quad (2.26)$$

where C_{tot} , i.e. the active material cost is computed accounting for the relative cost of each material type with respect to the cost of the NO20 steel of the core according to [81]:

$$C_{\text{tot}} = m_s + m_r + 3 \cdot m_w + 24 \cdot m_{pm} \quad (2.27)$$

This final stage ensures that the motor meets both performance and efficiency targets while minimizing losses across the driving cycle, thus optimizing the overall design.

2.4.5 MOGA results

The optimization results from the Multi-Objective Genetic Algorithm (MOGA) illustrate a trade-off between the two objective functions f_{Frugal} and f_{Dual} , evaluated over a total of 60 design solutions. The Pareto front obtained is shown in Figure 2.12, highlighting the influence of different design configurations on the active material cost C_{tot} and the maximum motor torque T_{max} .

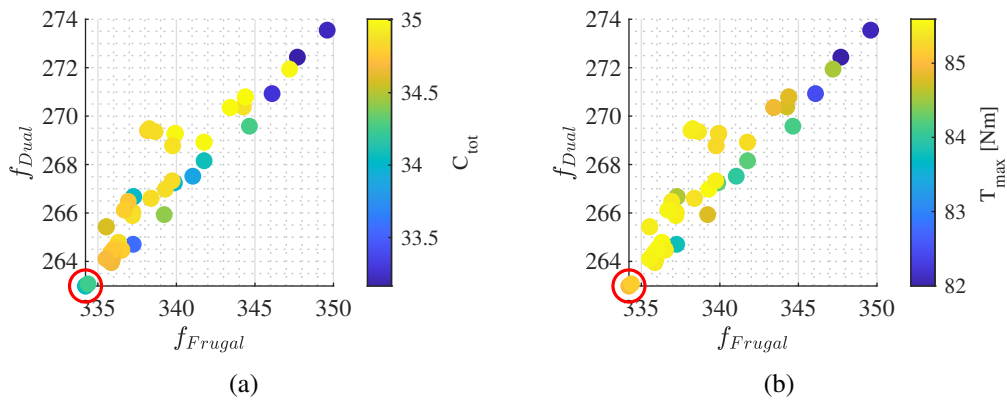


Fig. 2.12 MOGA objective functions results over an overall of 60 design solutions illustrating the (a) active material cost and (b) the maximum torque. Best solution in red circle.

The Pareto front exhibits a linear trend, where an improvement in f_{Frugal} leads to an increase in f_{Dual} , and vice versa. This behavior is directly related to the formulation of the objective functions: f_{Frugal} primarily favors efficiency at low speeds, as represented by the WLTC city cycle, while f_{Dual} accounts for operating points distributed over the entire speed range of the WLTC cycle. The most efficient design solutions tend to perform well at both high and low speeds. A few outliers are present, generally improving efficiency in Frugal mode only.

In Figure 2.12a the color gradient represents the cost of active materials. The trend suggests that lower-cost solutions (darker colors) are generally associated with higher f_{Frugal} values, implying that reducing material usage might compromise efficiency in Frugal mode. Conversely, higher-cost solutions tend to perform better across both objectives, especially in Dual mode.

The second plot 2.12b visualizes the effect of maximum torque T_{max} on the trade-off. A strong correlation emerges where higher torque values (lighter colors) are preferable for Dual mode operation, while Frugal mode configurations are generally associated with lower T_{max} .

To further investigate the design trade-offs, Figure 2.13 compares the active material cost (C_{tot}) with the weighted power losses ($P_{\text{loss,weighted}}$) in Frugal (a) and Dual (b) modes.

In Frugal mode 2.13a, designs with lower material cost generally exhibit higher losses, indicating that reducing active material compromises efficiency. The solutions with the lowest losses tend to be those with moderate material cost, suggesting an optimal region balancing cost and performance.

In Dual mode 2.13b), the relationship between material cost and losses is less pronounced, suggesting that efficiency in Dual mode (higher speed and load operations) is more strongly influenced by torque capability than by material cost. Higher-cost designs tend to exhibit better loss performance, but the variation is less significant than in Frugal mode.

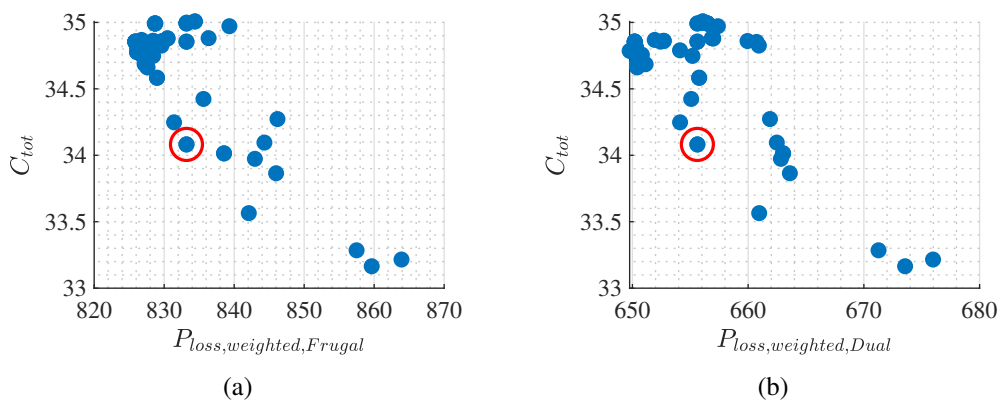


Fig. 2.13 Trade-off between the active material cost and the weighted power losses for the (a) Frugal and (b) Dual mode, evaluated over the MOGA design solutions. Best solution in red circle.

In this design, the primary objective is to maximize efficiency across a wide range of operating conditions. No additional verification of flux levels is required, as an inherently efficient machine over the entire operating range ensures that flux saturation is not a concern. For this specific application, the selected optimal solution minimizes power losses in both Frugal and Dual configurations, assuming an equal usage distribution between the two modes. Since this is a prototype, efficiency has been prioritized over cost considerations to ensure optimal energy performance during operation. The selection of the best solution, marked as (x_{best}) in the Pareto front, is based on minimizing the Euclidean distance from the ideal solution. Formally, it is defined as:

$$x_{\text{best}} = \arg \min_{x_i} d(x_i) \quad (2.28)$$

where the Euclidean distance $d(x_i)$ is given by:

$$d(x_i) = \sqrt{\sum_j \left(f_j(x_i) - f_j^* \right)^2} \quad (2.29)$$

with: - $f_j(x_i)$ representing the value of the objective function j for the solution x_i , - f_j^* being the ideal solution, defined as the minimum value of each objective function across all evaluated solutions:

$$f_j^* = \min_{x_i} f_j(x_i) \quad (2.30)$$

where the set of objective functions is:

$$j \in \{P_{\text{loss,Frugal}}, P_{\text{loss,Dual}}, 100 - T_{\text{max}}, C_{\text{tot}}\} \quad (2.31)$$

The trend of the solutions demonstrates the evolutionary improvement achieved through optimization. The final optimal design exhibits a significant reduction in f_{dual} , favoring improved efficiency in Dual mode, and a reduced f_{frugal} , with a balance between material cost and performance, avoiding excessive active material usage.

The selected optimal parameters are reported in Table 2.6, and the section of the optimal geometry is in Figure 2.14.

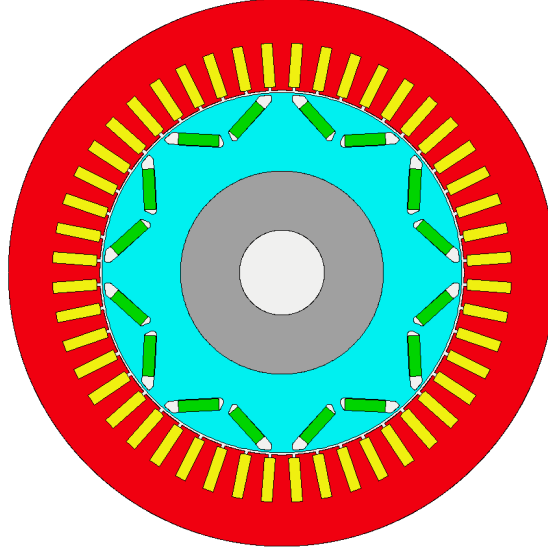


Fig. 2.14 Geometry of the EM optimal solution x_{best} .

Table 2.6 MOGA result parameters

Design variable x_i	Description	Optimal solution x_{best}
r_{so}	Stator outer radius	175.14 [mm]
r_{si}	Stator inner radius	116.62 [mm]
w_{so}	Slot opening width	1.17 [mm]
α_{pm}	PM V angle	41°
h_{pm}	PM thickness	3.71 [mm]
w_{pm}	PM width	12.93 [mm]
w_{w}	Web width, ratio	6.8 [mm]
w_{b}	Bridge thickness	0.71 [mm]

2.5 EDM optimal solution analysis

The performance of the selected optimal solution has been validated within its electromagnetic, mechanical, and thermal performance. The complete efficiency map has been obtained to assess the compliance of the proposed EDM with the required driving missions.

2.5.1 Electromagnetic performance

The electromagnetic performance of the optimal solution x_{best} is evaluated. A static analysis at a fixed operating point is conducted to assess magnetic flux saturation. The results are compared with those of the same motor but featuring a three-phase winding pattern, as reported in Figure 2.6, to highlight the central role of the multi-phase layout for the LVREV application.

A finite element analysis (FEA) was conducted to evaluate the magnetic flux density distribution (B) in the cross-section of the electric machine. The contour plot in Figure 2.15 illustrates the spatial variation of B , measured in Tesla [T], across the active magnetic components of the motor. For this analysis, the current level used in the simulation is close to the peak operating conditions $I_{\text{line,rms}} = 400$ A, ensuring that the machine is analyzed in full scenario. The results show that the stator tooth regions exhibit peak flux densities above 2.2 T, suggesting localized saturation. Rotor iron sections display a more uniform flux distribution, with values remaining below the typical saturation threshold for electrical steel and permanent magnets. The flux lines indicate smooth magnetic flow through the structure, with no significant flux leakage outside the active path.

Given these findings, no additional flux verification is required, as the motor design inherently ensures that the flux remains within an acceptable range under normal operation. The optimization process prioritizes efficiency, meaning that naturally avoids excessive saturation without the need for explicit constraints in the MOGA process.

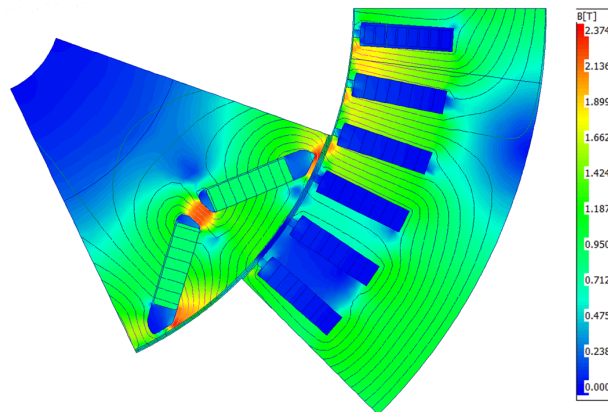


Fig. 2.15 FEA of magnetic flux density in [T] evaluated at $\omega = 1000$ rpm, current density $J = 12\text{A}/\text{mm}^2$.

The electromagnetic torque density is shown in Figure 2.16a, where it is compared with the three-phase configuration. The evaluation is performed at a shaft speed of 1000 rpm, with an RMS phase current of 450 A and a phase advance of 30 degrees. The RMS torque density is 4.88 Nm/kg with a ripple of 0.21 Nm/kg for the three-phase case, whereas in the six-phase configuration, it reaches 5.13 Nm/kg with a reduced ripple of 0.12 Nm/kg. Although the torque increase with the six-phase configuration is marginal, approximately 5%, the torque ripple is reduced by half, representing a significant improvement in vehicle comfort. The torque ripple is directly related to the harmonic content of the magnetomotive force (MMF), which is attenuated in the six-phase system.

The first 15 electrical harmonics of the MMF are shown in Figure 2.17. The results indicate that the amplitude of the fundamental harmonic is halved in the six-phase system compared to the three-phase configuration, while subsequent harmonic orders are significantly lower, except for the 5th and 7th harmonics. Since the MMF is primarily induced by the fundamental stator phase current, an increased number of phases leads to higher-order MMF harmonics with lower amplitudes.

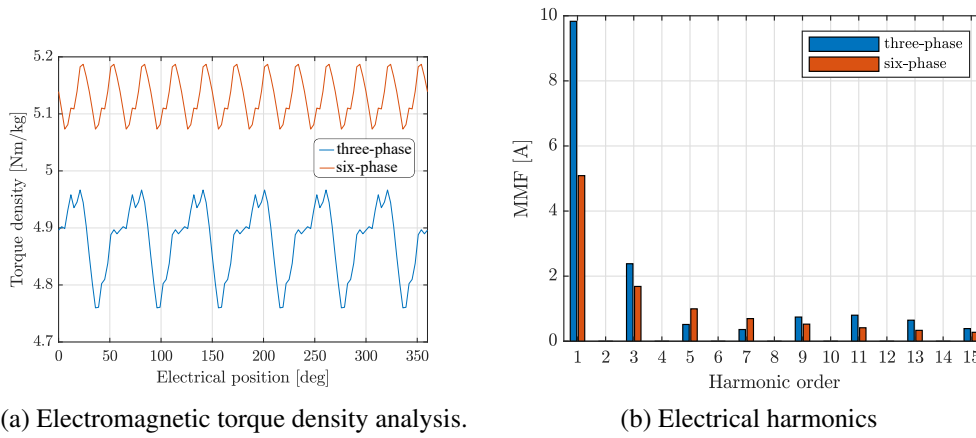


Fig. 2.16 6-phase vs 3-phase electromagnetic performance comparison. $\omega = 1000$ rpm, $I_{\text{phase,rms}} = 450$ A/mm², $\phi = 30$.

The back electromotive force (EMF) is presented in Figure 2.17 for the working point studied in the electromagnetic torque density analysis. Since the number of turns in series per phase in the six-phase is half of the three-phase, the induced back EMF, which is proportional to the variation of the flux linkage, will follow this ratio [74].

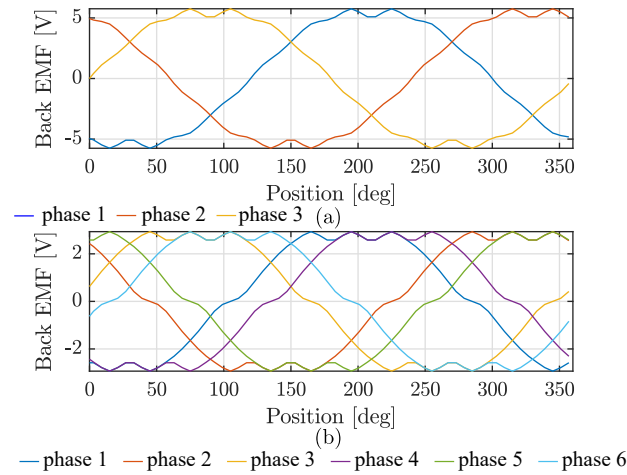


Fig. 2.17 Induced back EMF for the (a) three-phase and (b) six-phase machine.

In Figure 2.20, the efficiency maps of the optimal IPM solution x_{best} are shown for both Frugal and Dual modes. As observed from the plot, the proposed solution exhibits high efficiency, with a peak efficiency exceeding 97.5% and extensive high-efficiency regions.

For both configurations (where the two modes are simulated with different $I_{\text{dc, max}}$ values depending on whether one or two battery modules are onboard), the peak torque reaches 85 Nm, aligning with the requirements to meet the vehicle's gradability mission. The peak power in Dual mode is 47 kW, while in Frugal mode it is 29 kW. The base speed is 4500 rpm in Dual mode and 3000 rpm in Frugal mode. The main performance characteristics of the electric motor are summarized in Table 2.7.

The working points of the WLTC city cycle, executed in Frugal mode, and the WLTC cycle in Dual mode are scattered on the efficiency maps of the selected machine. The motor is capable of operating within the required driving missions for both configurations. On the other hand, the efficiency map of the three-phase configuration, shown in Figure 2.19, indicates that the torque-speed envelope of the motor in this setup is unable to encompass all the required operating points for the driving missions. The base speed is reduced to 2500 rpm, and the peak power is limited to 23 kW. Additionally, the overall high-efficiency regions are significantly reduced due to increased DC and AC losses.

Table 2.7 IPM performance

Specification	Symbol	Frugal mode	Dual mode
Dc supply voltage	V_{dc}	48 [V]	48 [V]
Maximum DC current	$I_{dc,cont}$	600 [A]	1200 [A]
Peak line current	$I_{phase,rms,max}$	350 [A]	450 [A]
Cont. line current	$I_{phase,rms,cont}$	250 [A]	250 [A]
Peak output power	$P_{EM,max}$	29 [kW]	47 [kW]
Peak torque	$T_{EM,max}$	85 [Nm]	85 [Nm]
Peak speed	$\omega_{EM,max}$	14000 [rpm]	14000 [rpm]
Base speed	$\omega_{EM,base}$	3000 [rpm]	4500 [rpm]
Cont. torque	$T_{EM,cont}$	40 [Nm]	40 [Nm]
Cont. power	$P_{EM,cont}$	20 [kW]	30 [kW]
Max. efficiency	$\eta_{EM,max}$	97.8	97.6

The air gap was set to 0.7 mm, a typical compromise in IPM traction motors between torque density and mechanical robustness. A first estimate of the required tangential shear stress τ to meet the torque target can be computed as:

$$\tau = \frac{T}{2\pi R_{ro} l} \quad (2.32)$$

where $T = 85$ Nm is the maximum torque, $R_{ro} = 58$ mm the mean air gap radius, and $l = 105$ mm the stack length. Substituting values, $\tau \approx 2.22$ kPa, which is coherent with typical IPM shear stress values [90].

Similarly, the active length was fixed at $l = 105$ mm, determined by the mechanical envelope of the EDM housing. To validate this choice, the specific torque per active volume is computed:

$$T_s = \frac{T}{V_{active}}, \quad V_{active} = \pi(R_{ro}^2 - R_{ri}^2)l \quad (2.33)$$

This yields $T_s \approx 134$ kNm/m³, a value consistent with IPM designs for compact electric traction applications [33].

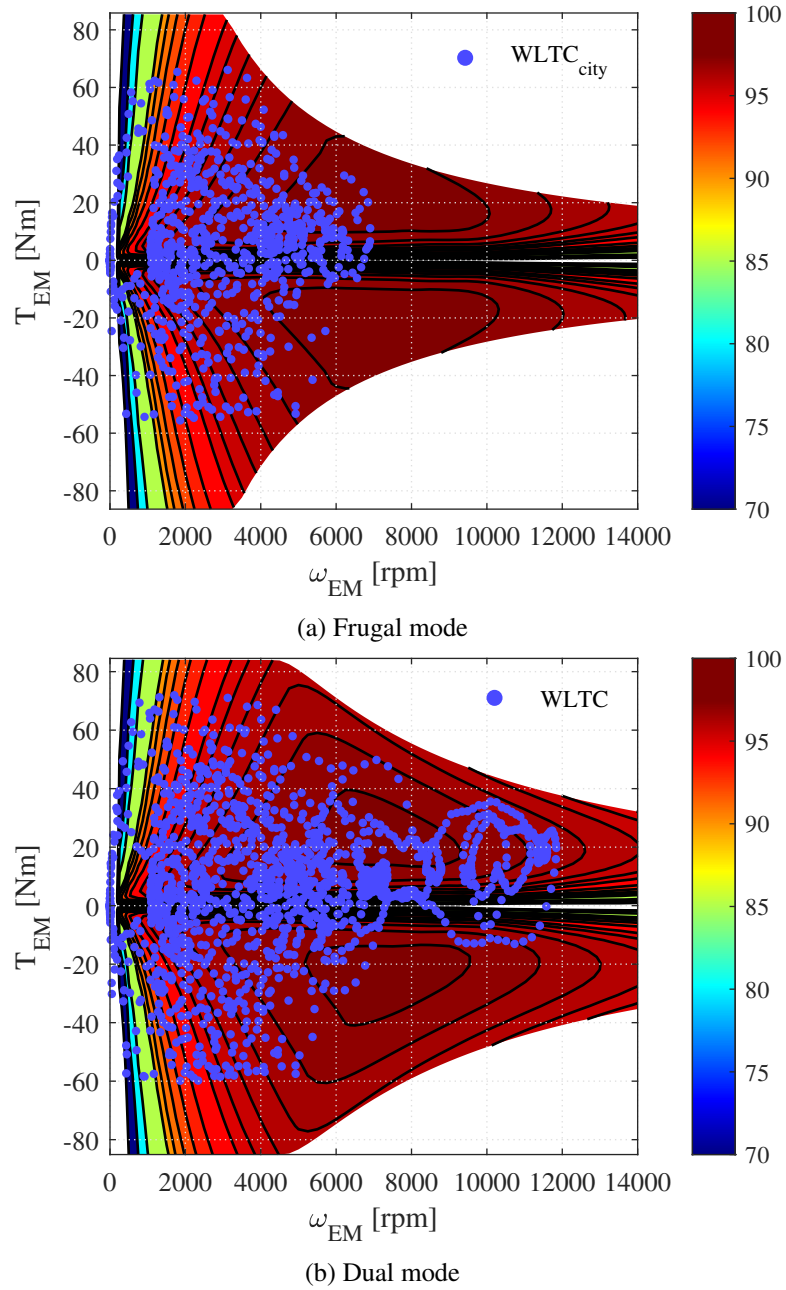


Fig. 2.18 Torque-speed maps with the WLTC and WLTC city cycle overlapped: (a) Frugal configuration and (b) Dual configuration.

2.5.2 Mechanical analysis

The mechanical stresses on the rotor bridges are primarily induced by centrifugal forces generated by the cavities housing the permanent magnets (PMs) within the

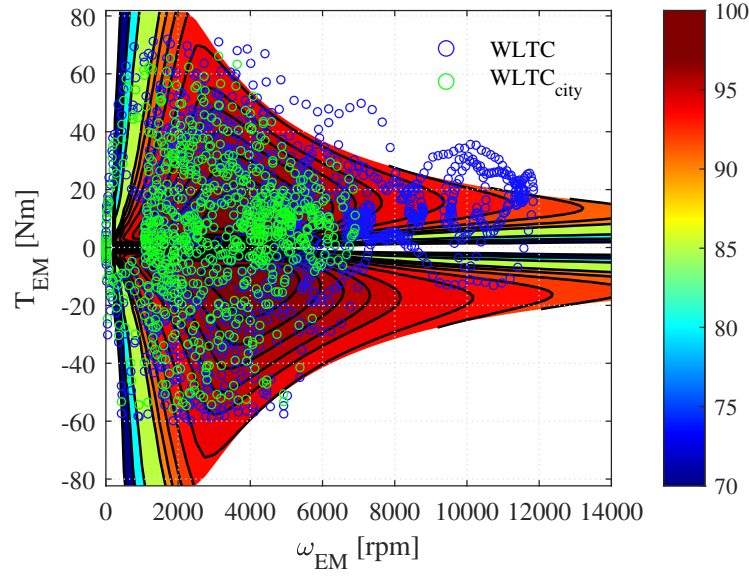


Fig. 2.19 Torque-speed maps with the WLTC and WLTC city cycle overlapped, 3-phase configuration.

rotor structure. A detailed static structural finite element analysis (FEA) was conducted in Ansys under steady-state conditions at a maximum rotational speed of 14000 rpm. The analysis assumes that electromagnetic forces, vibrations, and rotor dynamic effects are negligible.

In this evaluation, the PMs are considered to be bonded within their cavities with an adhesion factor of 0.3. The von Mises stress distribution across the rotor structure was assessed to verify compliance with the material constraints in Figure 2.20a. The rotor laminations are made of NO20 electrical steel, which has a yield strength (σ_y) of 445 MPa. The maximum von Mises stress observed in the rotor remains within acceptable limits, ensuring a safety factor (SF) of 2.6.

Figure 2.20b presents the displacement analysis results, showing that the maximum radial deformation is 0.016 mm. Given the air gap of 0.7 mm, this displacement is well within the permissible limits, ensuring reliable rotor operation without risk of mechanical interference.

To reduce torque ripple, a 4 segment skewing is performed according to:

$$\vartheta_{sk} = \frac{1}{N_p} \cdot \frac{2\pi}{N_s} = 7.5^\circ \quad (2.34)$$

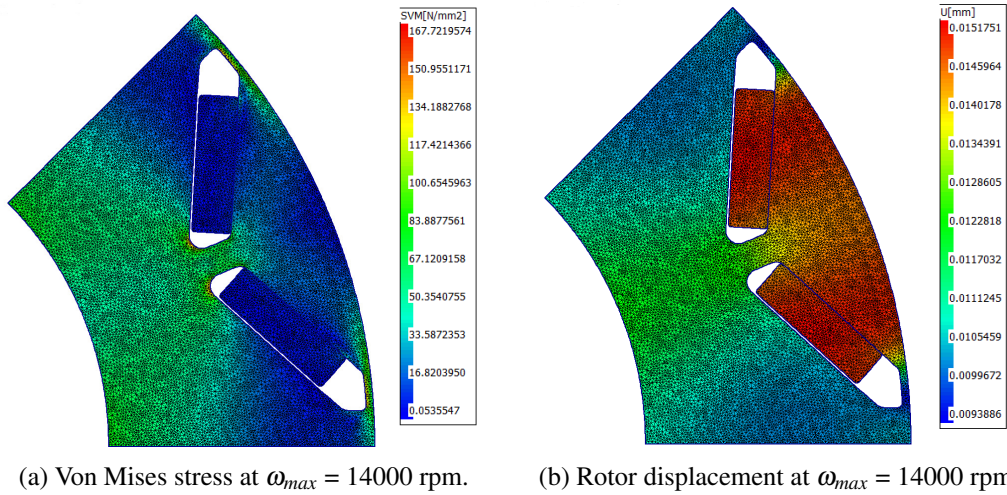


Fig. 2.20 Mechanical FEM analysis of the rotor at maximum speed.

The mechanical coupling between the rotor and the shaft has been verified through a detailed interference analysis. COMSOL Multiphysics was employed for the numerical model using the Solid Mechanics module. Indeed, a contact pair was defined between the shaft and the rotor with a friction coefficient of 0.05 considering a cool press mounting with oil in steel. Model symmetry was exploited, thus a half-section of the stator-shaft assembly through the axial plane was analyzed and the results were properly scaled. The shaft was supported by two bearings, one on each axial side. Since the study of the variation of the contact pressure and the transmitted torque concerning the shaft speed is of primary interest, a rotating frame was defined which accounts for centrifugal forces. Finally, the radial interference will be evaluated at different values, to select a proper manufacture tolerance in successive steps.

The results for the V-shape geometry for contact pressure, transmitted torque, and maximum Von Misses Stresses are in Figure 2.21 as a function of the shaft speed. Here the maximum speed limit to sustain the torque load of 100 Nm has been reduced significantly compared with the simplified model. From Figure 2.22, the stresses in the rotor are concentrated in the V-shape region where the magnets are placed. An optimal interference must be around 25 μm , since the maximum speed limit is located at 14000 rpm to transmit the maximum torque. However, at high speed, the machine operates in the flux-weakening region, thus the torque request is considerably lower than the peak value. Consequently, the risks of losing contact between the torque and shaft are minimized. Although an interference of 50 μm can withstand speeds

above 20000 rpm, the maximum stress is considerably increased reaching the yield strength limit around 16000 rpm. Moreover, the electrical properties of the steel are degraded with increased stress due to premature saturation of the magnetic flux [105]. From the analysis, it emerges that an interference level of $25 \mu\text{m}$ can be selected to transmit the required torque at the required maximum speed.

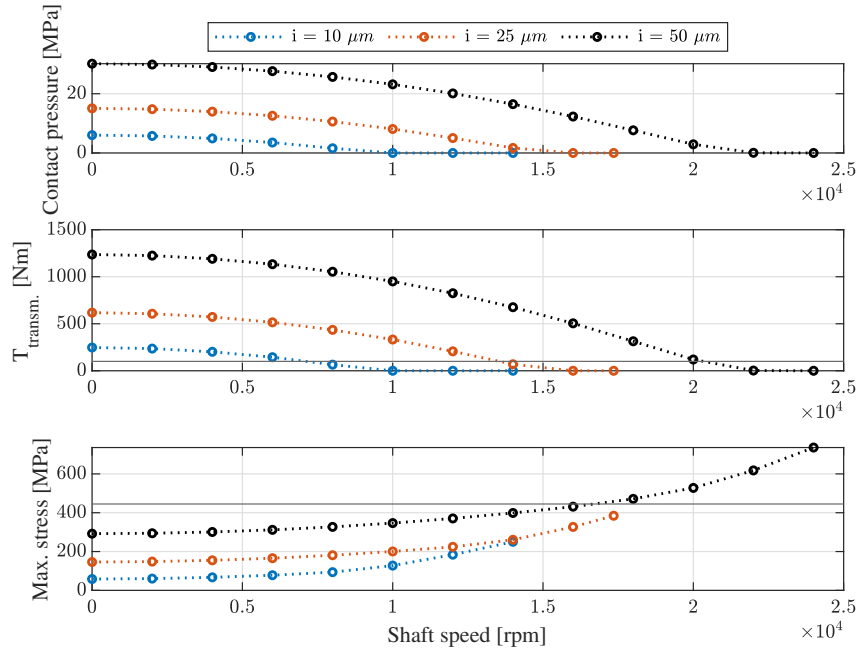


Fig. 2.21 Results for the interference fit analysis on the V-shape rotor as a function of shaft speed.

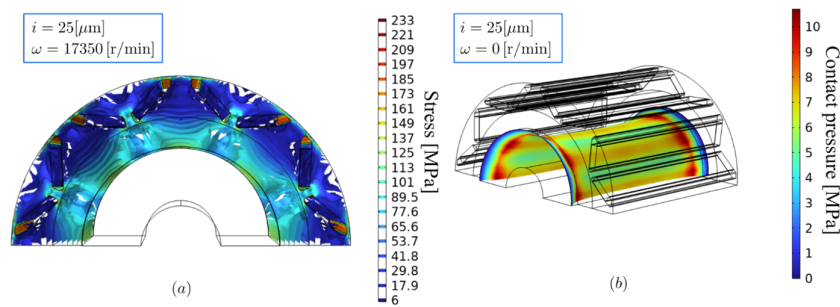


Fig. 2.22 FEA results for the distribution of (a) Von Misses Stresses distribution at $i=25 \mu\text{m}$ and $\omega = 17350 \text{ rpm}$ and (b) Contact pressure at $i=25 \mu\text{m}$ and $\omega = 0 \text{ rpm}$.

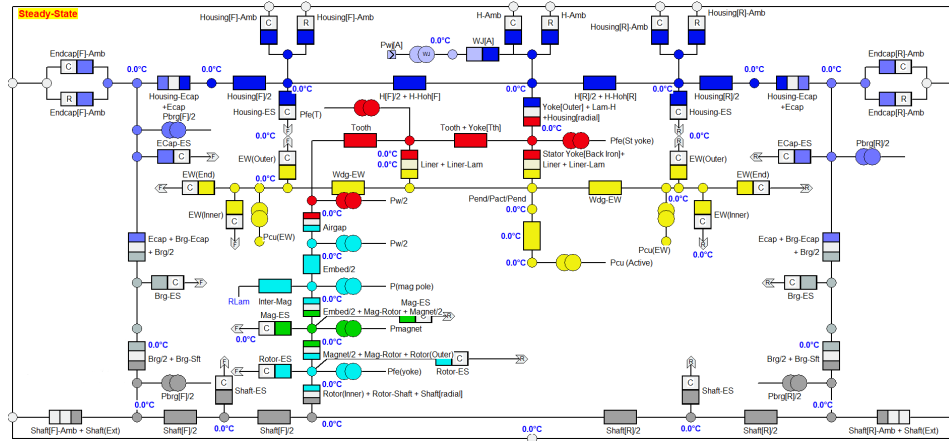


Fig. 2.23 Lumped parameter thermal network of the electric motor.

2.5.3 Thermal performance

The thermal performance of the proposed electric motor has been evaluated through the implementation of a lumped parameter thermal network (LPTN), as shown in Figure 2.23. The developed LPTN model, implemented in MotorCAD, consists of 443 thermal nodes distributed across the motor geometry to accurately capture heat generation and dissipation mechanisms. The thermal analysis aims to ensure that the maximum operating temperature remains within the limits defined by the insulation class.

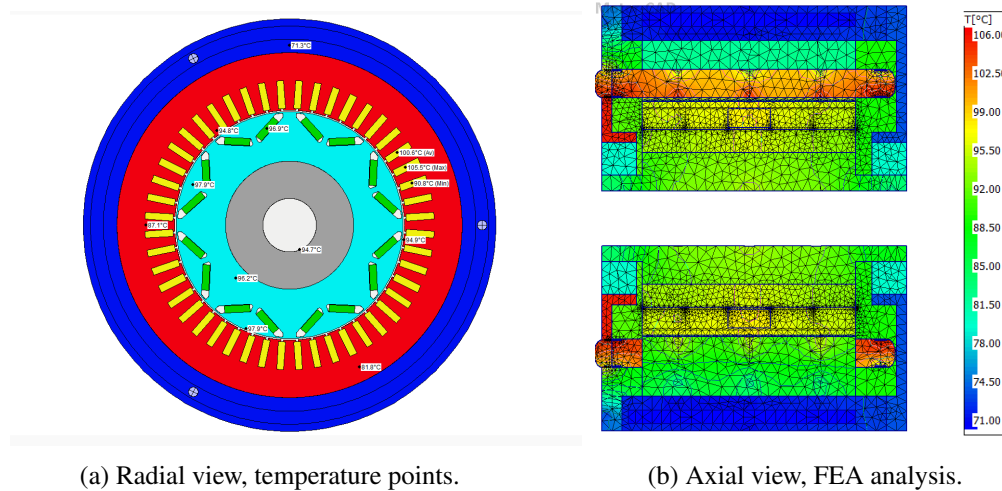


Fig. 2.24 Steady-state thermal analysis at vehicle speed constant 130 km/h in Dual mode, $\omega_{EM} = 12500$ rpm, $T_{EM} = 23$ Nm,

A steady-state thermal analysis was conducted at 130 km/h in Dual mode (as the most critical continuous condition), with an electric machine speed of 12500 rpm and a torque of 23 Nm, as illustrated in Figure 2.24. The results demonstrate a well-balanced thermal distribution, with the highest temperatures (106 °C) localized in the stator end windings, while other components, such as the rotor and magnets, remain within safe operating conditions. This trend is confirmed by the FEA simulation reported in Figure 2.24b. The maximum temperature recorded over the WLTC driving cycle (Dual mode) remains consistently below 180°C, ensuring the motor operates within the thermal constraints of the winding insulation class.

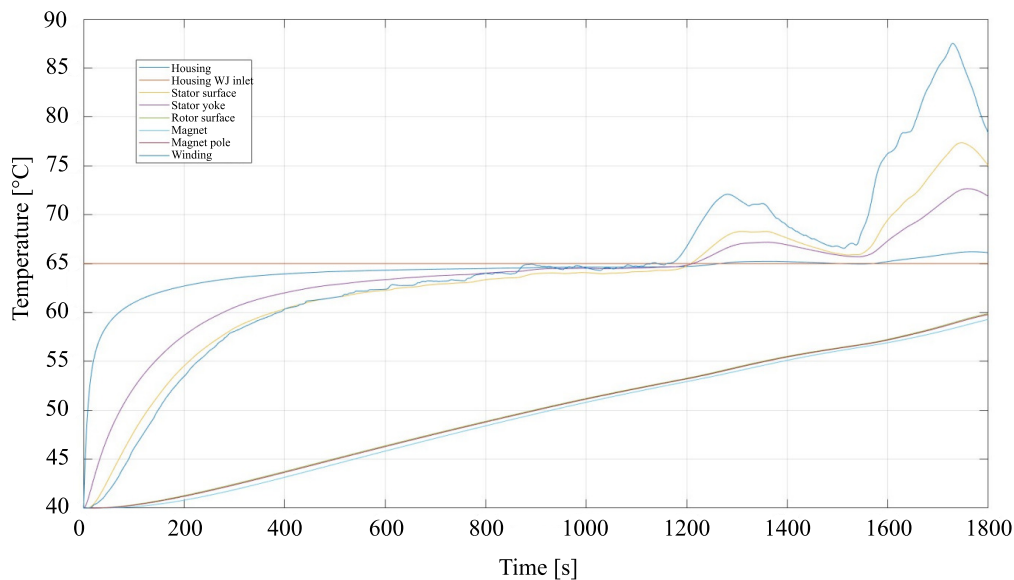


Fig. 2.25 Transient thermal simulation, WLTC driving cycle in Dual mode.

The transient thermal response is reported in Figure 2.25, showing the evolution of temperature over time for different motor components. The winding hotspot exhibits the highest thermal rise, reaching a peak of approximately 85°C after 1800 seconds. The housing water jacket inlet temperature is maintained at 60°C, in accordance with the cooling system specifications. The magnet and rotor temperatures remain well below critical values, which is crucial for maintaining the integrity of the permanent magnets and reducing the risk of demagnetization.

The motor's cooling system plays a fundamental role in managing the thermal behavior of the machine. As summarized in Table 2.8, the cooling system adopts an active water-jacket cooling approach, with a fluid volume flow rate of 6 l/min and a single parallel flow path configuration. The coolant fluid (EGW 50/50) exhibits a

Table 2.8 Cooling system specifications

Specification	Value
Housing water jacket type	Active Cooling Only
Flow direction	Front → Rear
Fluid volume flow rate	6 [l/min]
Inlet temperature	60 [°C]
Reference shaft speed	3000 [rpm]
Fluid type	EGW 50/50
Thermal conductivity	0.411 [W/m·°C]
Parallel flow paths	1
Number of flow channels	3.886
Flow area (per channel)	106.9 [mm ²]

thermal conductivity of 0.411 W/m°C, ensuring efficient heat dissipation from the housing. The flow direction is front-to-rear, optimizing heat extraction from the most thermally stressed areas. The flow channels and distribution are designed to ensure uniform heat dissipation across the motor casing.

Overall, the thermal assessment confirms that the proposed motor operates within safe thermal limits across the considered driving cycles and mission profiles.

2.6 EDM construction

The design of the electric drive module (EDM) has been developed to meet the optimal design solution output of the design methodology and integration constraints, ensuring compatibility with the existing Fiat 500e housing. The primary challenge in this design was to accommodate a six-phase low-voltage electric machine within the original casing while maintaining efficient thermal management.

To achieve this, a detailed CAD model was created. The proposed EDM features a reduced stator diameter and length comparable to those of the original motor. Since the motor is installed inside the existing case, a custom internal cooling jacket has been introduced. This solution not only ensures a seamless mechanical interface between the new motor and the original housing but also provides the required cooling performance, to accomplish all the driving missions defined in Table 2.8.

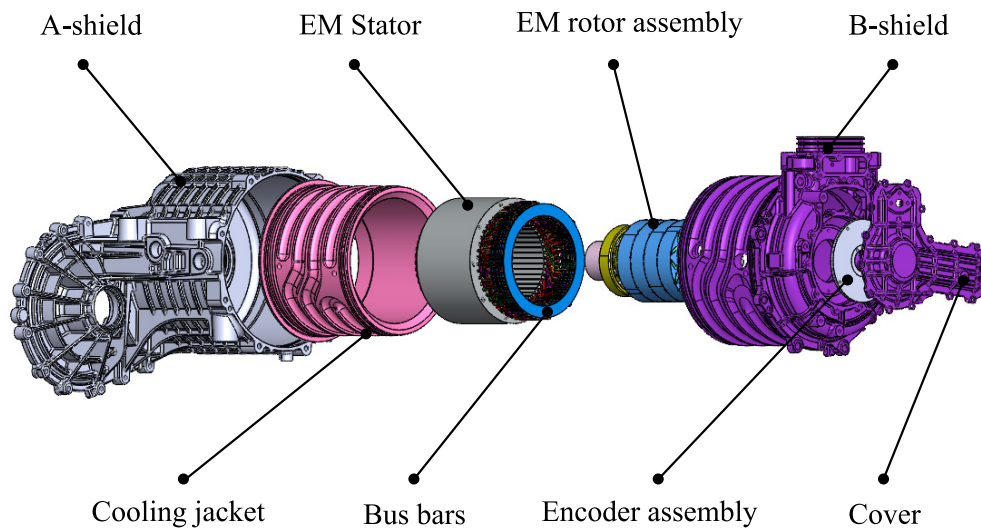


Fig. 2.26 EDM CAD, exploded view.

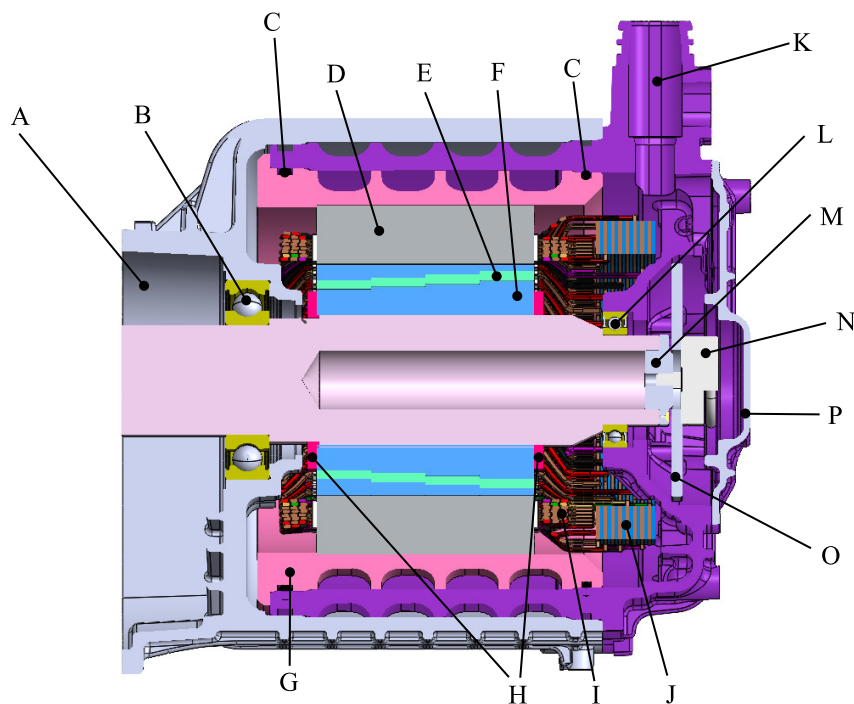
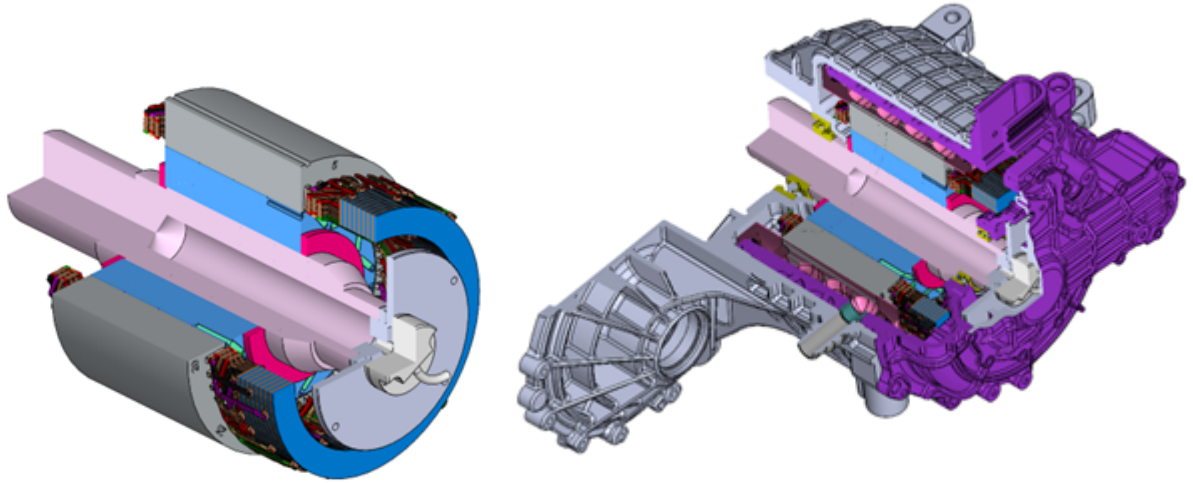


Fig. 2.27 EDM CAD assembly, cross-section. The labeled components of the electric motor are as follows: (A) A-shield, (B) Ball bearing, (C) Sealing rings, (D) EM stator, (E) Permanent magnet (N42SH), (F) EM rotor (4 rotor slices), (G) Cooling jacket, (H) Rotor end rings, (I) Hairpin winding, (J) Bus bars, (K) B-shield, (L) Ball bearing, (M) Encoder rotating magnetic actuator, (N) Encoder stator, (O) Encoder stator supporting flange, (P) End cover.



(a) Sectional view of EDM stator, rotor, winding, bus-bars, encoder sensor, and drive shaft. (b) Sectional view of the complete EDM assembly.

Fig. 2.28 Sectional view of the EDM assembly CAD model.

The rotor laminated stack has been designed to be compatible with the NP shaft, maintaining the same bearing arrangement as the standard production EDM. This design decision ensures mechanical stability and facilitates integration into the existing drivetrain without requiring modifications to the main transmission components.

Figure 2.26 presents an exploded view of the EDM assembly, highlighting both standard components - such as the A-shield, B-shield, and shaft, which are derived from mass production - and custom-developed components, including the cooling jacket, stator, rotor, and specialized electrical interfaces.

Particular attention has been given to the bus bars layout, as illustrated in Figure 2.30a. These bus bars were developed in collaboration with Tecnomatic, a specialized supplier of hairpin windings [106]. The structure consists of eight copper layers responsible for connecting the six-phase windings and the two neutral star points. The copper conductors are insulated by ULTEM plastic layers, manufactured using additive manufacturing techniques, ensuring electrical insulation and mechanical stability.

The EDM also incorporates a differential analog encoder, which consists of a rotating magnetic actuator mounted on the shaft and a stator assembly flanged to the B-shield. This setup ensures precise rotor position feedback to the two inverters.

A comprehensive sectional view of the EDM is depicted in Figure 2.27, where the integration of the cooling system, rotor, stator, and bus bars is detailed. A complete list of components, including bearings, seals, and retaining rings, is provided in the sectional view, giving a comprehensive view of the system assembly and integration.

In Figure 2.29, the prototypes of one rotor slice, and of the stator and winding subassembly are reported.

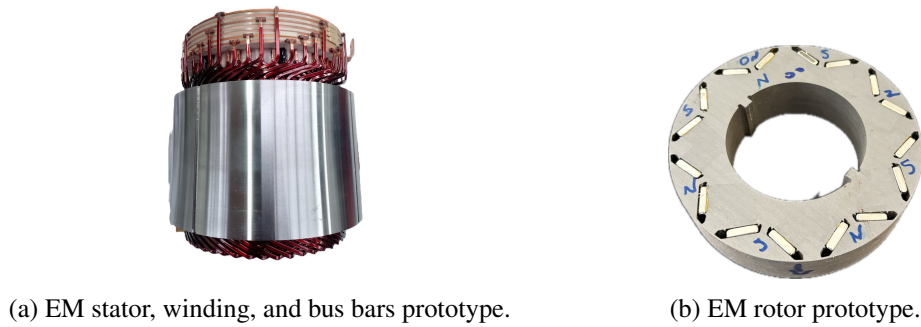


Fig. 2.29

2.7 Torque control strategy for the Six-Phase IPMSM

The complete traction system adopts a dual-inverter configuration composed of two off-the-shelf 48 V inverters, each driving a three-phase winding set. This architecture is designed to leverage the modularity of dual-inverter technology, enabling efficient operation, load balancing, and simplified implementation of fault-tolerance strategies. Both inverters are synchronized through a shared rotor position signal obtained from a single encoder, with a compensation offset of 30 electrical degrees to account for the spatial displacement between the two winding sets. Each inverter receives an independent torque reference, allowing decoupled current control for the respective three-phase subsystems while ensuring coordinated overall torque production.

The selected inverter modules fulfill the requirements of the low-voltage electric vehicle platform:

- Continuous operation (S1 Duty): 300 A RMS per phase at 48 V, corresponding to a continuous apparent power of 16.8 kVA with air cooling.

- Short-time operation (S2 Duty): Peak current of 600 A RMS per phase for up to 15 seconds, enabling a transient apparent power of 33.5 kVA.

Although the implementation details of the low-level control are beyond the scope of this dissertation, the fundamental principles are briefly outlined here to provide context.

The theoretical foundation adopted for the control design is based on the Vector Space Decomposition (VSD) approach [107], which allows the transformation of the six-dimensional stator current vector into four orthogonal subspaces:

$$\mathbf{i}_{abc,abc} = \begin{bmatrix} i_{a1} & i_{b1} & i_{c1} & i_{a2} & i_{b2} & i_{c2} \end{bmatrix}^T \xrightarrow{T_{VSD}} \begin{bmatrix} i_d & i_q & i_{z1} & i_{z2} \end{bmatrix}^T. \quad (2.35)$$

Among these, only the dq subspace is responsible for torque generation, while the z_1 and z_2 components are associated with non-torque-producing harmonic subspaces. In order to ensure optimal electromagnetic performance, the control scheme enforces the suppression of these components:

$$i_{z1} = i_{z2} = 0. \quad (2.36)$$

Torque generation is then regulated through conventional Field-Oriented Control (FOC) applied to the fundamental dq components, using the standard torque expression for an IPM machine:

$$T_e = \frac{3}{2}p (\psi_d i_q + (L_d - L_q) i_d i_q), \quad (2.37)$$

where L_d , L_q are the d - and q -axis inductances, ψ_d is the flux linkage in the d -axis, and p is the number of pole pairs. The current references i_d^* and i_q^* are defined according to the Maximum Torque Per Ampere (MTPA) strategy in the low-speed region, and Field Weakening (FW). Each three-phase subsystem is controlled independently through a dedicated FOC loop, and coordinated modulation strategies (e.g., space vector PWM) ensure phase voltage balancing and DC bus utilization.

The overall Simulink control model developed for this architecture includes current regulators (PI controllers) in the dq frame, Clarke and Park transformations

for both windings, and voltage saturation blocks to account for inverter limitations. The torque response under step references is shown in Fig. 2.30, confirming the capability of the system to track commands accurately and suppress cross-coupling effects.

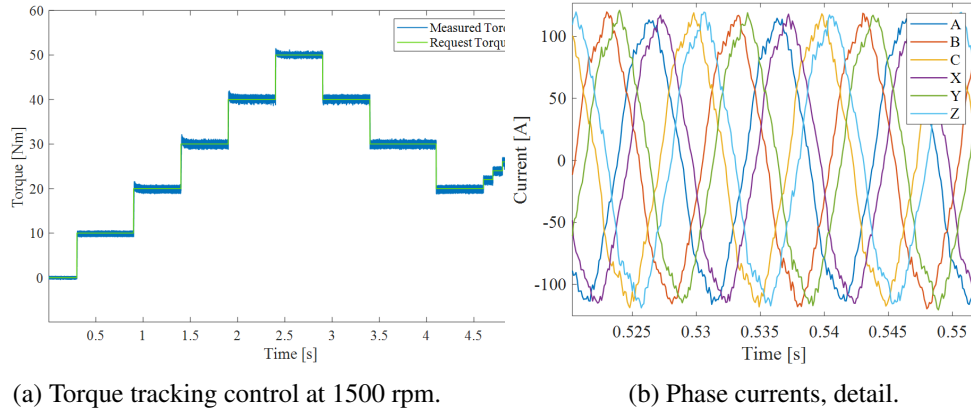


Fig. 2.30 VSD torque tracking control at 1500 rpm.

2.8 Low voltage reconfigurable vehicle performance

The performance of the vehicle have been assessed using a forward longitudinal vehicle model developed in MATLAB/Simulink. The efficiency maps of the designed EDM in both Frugal and Dual modes are integrated into the model to evaluate performance and energy consumption at the vehicle level.

At each simulation time instant, the driver model, implemented as a Proportional-Integral controller, compares the current speed with the reference imposed by the driving cycle (e.g., WLTP, RDE) and determines the required torque. This reference signal is sent to the powertrain controller, which regulates the torque demand delivered by the electric motor. The traction and braking forces are applied to the front-driven wheels, while the inverter supplies the motor and defines the power demand from the battery pack. The final drive consists of a single-gear transmission with a fixed efficiency of 97%, and the differential is assumed to be ideal, ensuring a realistic but computationally efficient simulation framework.

Battery losses are modeled using an electrical equivalent circuit with an internal resistance R_i and an ideal voltage source V_0 , whose parameters are derived from literature on 48 V battery packs with similar chemistry.

To validate the forward vehicle model, experimental characterization of the original FIAT 500e powertrain was conducted at the four-axis powertrain testbed of CARS@Polito (Figure 2.31). The vehicle's wheel hubs were connected to four dynamometers equipped with high-resolution torque sensors. The electrical energy consumption was recorded in real-time through current measurements. At 20 fixed vehicle speeds, the road grade was progressively increased to span the entire torque range. Mechanical output power was evaluated via torque measurements at the dynamometers, while the input electrical power was acquired from battery-side current and voltage data. These measurements enabled the construction of a detailed efficiency map for the entire propulsion system—comprising battery, inverter, electric motor, and mechanical transmission. Figure 2.32 compares the experimental and simulated profiles of vehicle speed and battery power, obtained from tests conducted on the powertrain testbed, showing a consistent match between the simulated and recorded power profiles.

The resulting loss map of the electric powertrain was integrated into the forward vehicle model. The model was subsequently validated using experimental data from the FIAT 500e Low Range BEV, with full access to the vehicle's CAN network. Over the WLTC driving cycle, the model estimated an energy consumption of 13.2 kWh/100 km, in close agreement with the manufacturer's reported value of 13.0 kWh/100 km.

Following this validation, the efficiency map of the newly designed six-phase low-voltage motor, along with the battery model of the reconfigurable LVREV vehicle, was incorporated into the framework. This enabled reliable simulation-based assessment of the LVREV's energy consumption across multiple driving scenarios.

The WLTC simulations assume dry asphalt conditions at an ambient temperature of 20°C, with the test mass including curb weight, a 100 kg occupant, and an additional 15% of the maximum payload. Traffic conditions are not accounted for. The results of the LVREV design in terms of Frugal and Dual mode performance are summarized in Table 2.9. The reported energy consumption values consider the tank-to-wheel efficiency of the vehicle, used for battery sizing, and the plug-to-wheel



Fig. 2.31 Fiat 500e donor vehicle characterization in CARS@Polito test bench.

efficiency, which accounts for a fixed 95% charger efficiency. The battery power demand evolution over time for the Frugal and Dual modes is shown in Figure 2.33. The electric power requested from the battery aligns with the maximum current rating of the selected cells, confirming that the proposed dual-inverter architecture is fundamental for meeting power requirements. The difference in the curb weight between Frugal and Dual mode represents the target battery module vehicle. In the final prototype, however, after battery case refinement and prototype construction, the actual module achieves a weight of 70 kg. To facilitate handling during swap operations, a purpose-built electrically-actuated trolley has been developed. This tool enables safe and controlled battery extraction without requiring manual lifting, even in the case of larger modules. Furthermore, the battery modules can be subdivided into smaller and lighter sub-packs, allowing greater flexibility in packaging and facilitating handling or replacement operations.

The modular nature of the proposed vehicle architecture brings two key advantages. In Frugal mode, the reduced vehicle weight ensures a competitive urban range, while Dual mode enables twice the battery capacity and motor power with only a minor weight increase. In both cases, the achieved performance meets or exceeds the imposed design targets, in terms of maximum speed, range, and acceleration capabilities.

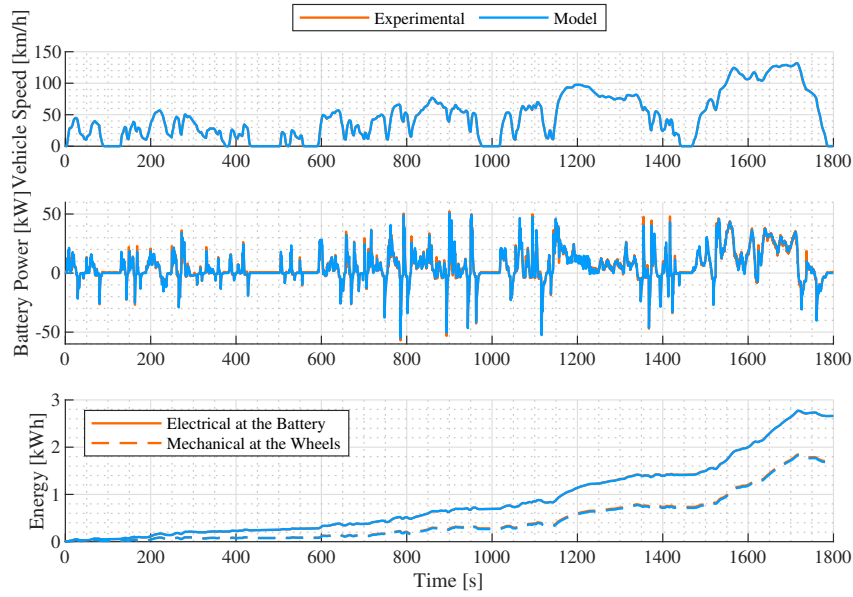


Fig. 2.32 Experimental and simulated time profiles of vehicle speed, battery power, and energy over the WLTC driving cycle, performed by the Fiat 500e donor vehicle

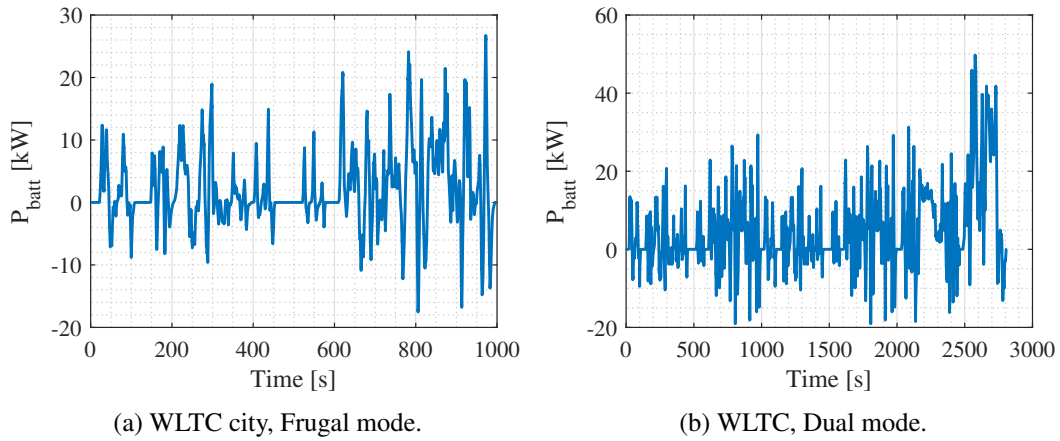


Fig. 2.33 LVREV Battery power from forward vehicle model simulations.

2.9 Final remarks

A novel powertrain architecture has been proposed to enhance sustainable and affordable urban mobility. The Low Voltage Reconfigurable Electric Vehicle introduces a fully low-voltage powertrain, enabling safe and efficient battery swapping operations. A key feature of this platform is the custom-designed multi-phase electric drive

Table 2.9 Vehicle performance comparison between SRV Dual Mode and SRV Frugal Mode

Characteristics	SRV Dual Mode	SRV Frugal Mode
Top speed	130 [km/h]	100 [km/h]
WLTC-city Range	280 [km]	150 [km]
Energy Cons. WLTC-City	8.52 [kWh/100km]	7.9 [kWh/100km]
WLTC Range	200 [km]	115 [km]
Energy Cons. WLTC	12.0 [kWh/100km]	10.6 (100 km/h max) [kWh/100km]
Voltage	48 [V]	48 [V]
Curb weight	1000 [kg]	900 [kg]
GVW	1350 [kg]	1250 [kg]
Battery Size	23.8 [kWh]	11.9 [kWh]
Net power	47 [kW]	29 [kW]
Torque @ wheels	867 [Nm]	867 [Nm]
Climbing 15 km/h slope (GVW)	20 [%]	20 [%]
Climbing 0.5 m/s ² slope (GVW)	20 [%]	20 [%]
Acc. time: 0–50 km/h	5.3 [s]	5.3 [s]
Acc. time: 0–90 km/h	10.9 [s]	14.5 [s]

module, equipped with a dual-inverter topology that allows reconfigurability for different driving missions while ensuring fault tolerance and operational safety.

In this framework, multi-objective optimization algorithms have been employed to design a custom EDM, addressing the strict constraints imposed by low-voltage operation, reconfigurability, and high efficiency. The proposed EDM features an advanced multi-phase hairpin winding, optimized to deliver the required performance at the vehicle level while maintaining compatibility with low-voltage power electronics.

The optimization result has been extensively analyzed and validated, incorporating electromagnetic, mechanical, and thermal evaluations at both the component and vehicle levels. The forward vehicle model, including the optimized efficiency maps, has demonstrated compliance with energy consumption and performance targets, confirming the feasibility and benefits of the proposed architecture.

The results highlight how the electrification of powertrain components enables the development of novel architectures and layouts. The proposed design methodology and technological solutions pave the way for wider adoption of electric mobility, particularly in urban environments where flexibility and cost-effectiveness are crucial.

Chapter 3

Preview based traction control system for battery electric vehicles

The transition to electrified powertrains enables advanced control capabilities for wheel torque, due to the inherently faster and more precise torque generation of electric machines compared to internal combustion engines and traditional braking systems. This enhanced controllability opens the way for advanced vehicle dynamics and active safety systems that go beyond conventional reactive strategies.

While optimization techniques have traditionally supported component-level design, as discussed for the optimal EDM design, their application is increasingly extending into real-time control strategies. This allows for the development of predictive control solutions that adapt to varying operating conditions.

In this context, the focus of this chapter moves from the design of electric powertrains to their real-time control potential. A novel traction control strategy based on preview-based Nonlinear Model Predictive Control (NMPC) is proposed and investigated. This approach exploits forthcoming information on road profile and tire–road friction to anticipate critical conditions, enhancing traction control on irregular or low-friction surfaces.

The section presents the methodology, simulation results, and experimental validation of the proposed NMPC-based traction control system.

3.1 Traction control system for BEVs, state of the art

Traction control systems (TCSs) are active safety functions aimed at preventing excessive wheel slip during vehicle acceleration, with the ultimate goal of enhancing traction capability and maintaining stability. Their operation relies on precise wheel torque regulation to track or constrain the slip ratio within desired limits, especially under varying surface conditions such as low- μ or split- μ scenarios. Traditionally, TCSs have been implemented using internal combustion engine torque modulation in combination with friction brake actuation. However, the transition to electric propulsion has introduced new opportunities for improved performance.

Electric motor drives are inherently characterized by a faster and more accurate torque response compared to ICEs and hydraulic braking systems. As a result, the effectiveness of both TCS and anti-lock braking systems (ABS) can be significantly enhanced in full electric vehicles, particularly due to their capability to perform high-frequency torque modulation—often exceeding 10 Hz—compared to the 3–10 Hz typical of conventional actuation [108, 56].

In ICE systems, torque modulation can be achieved either at the combustion cycles level (fast path, depending on engine speed) or through throttle and boost control (slow path, <1Hz). However, the mechanical filtering effect of drivelines, comprising clutches, flywheels, gearboxes, drive shafts, and differentials, significantly attenuates the effect of high-frequency torque input at the wheel. As a result, effective torque modulation for drivability purposes typically occurs below 10 Hz in ICEs. Furthermore, ICE drivetrains are characterized by significant delay (typically varying between 20 and 200 ms, depending on the engine speed [109]). Electric motors have torque bandwidths in the order of hundreds of Hz to 1 kHz (at the inverter level). However, the effective bandwidth of torque modulation in electric vehicles is not only defined by the electrical capabilities of the actuators, but by the dynamic response of the mechanical system from motor to tire-road contact. In conventional EVs with on-board motor configurations, the torsional compliance of drive shafts, differentials, and tire deformation acts as a low-pass filter. As presented by [110] and [61], these components restrict the effective bandwidth for torque control to approximately 10 - 20 Hz. Beyond this range, torque oscillations are absorbed by the drivetrain's elasticity or can excite high-frequency leading to ride quality degradation. In in-wheel motor (IWM) architectures, as analyzed in Murata [30], the removal of shafts and differentials significantly shortens the mechanical transmission path,

increasing the torque modulation capabilities. This setup shifts the first torsional resonance frequency upward, with dominant modes often observed in the 40 - 80 Hz range. However, this benefit is offset by the increase in the unsprung mass, which can introduce new coupling effects with ride dynamics. As a result, although the mechanical system in IWM vehicles allows higher torque modulation frequencies, the effective and safe control bandwidth remains typically within 20 - 30 Hz.

In the literature, traction control is often formulated as a continuous wheel slip regulation problem, where various strategies have been proposed. These range from rule-based or fuzzy logic methods to continuous-time controllers explicitly regulating the slip ratio. Common feedback approaches include gain-scheduled proportional-integral-derivative (PID) and linear quadratic regulator (LQR) controllers [111, 112], as well as sliding mode controllers [113, 114]. More advanced designs employ model predictive control (MPC), which allows optimizing the control input over a prediction horizon while handling system constraints [115, 116].

The comprehensive survey by Ivanov et al. highlights how individually controlled electric motors open up new possibilities in TCS design, for both architectures based on in-wheel or on-board motors [56]. Their analysis distinguishes between torque-based and slip-based control strategies.

In this context, the recent integration of connectivity and perception technologies in intelligent vehicles has further expanded the potential of traction control strategies. Vehicle-to-everything (V2X) communication enables real-time data exchange between the ego vehicle, other road users, and the infrastructure, thus allowing early detection of upcoming low-friction surfaces [117, 118]. Concurrently, production vehicles are increasingly equipped with exteroceptive sensors (e.g., cameras and lidar) capable of scanning the road environment ahead. These sensors can be used to supply information on the road profile, which, when combined with estimation algorithms, contributes to the reconstruction of both friction and elevation maps [119–121].

Such real-time preview information, when effectively integrated into the control architecture, can significantly enhance active safety functions such as TCS, ABS, stability and ride comfort controllers [53, 61]. In particular, MPC has emerged as a highly suitable methodology for exploiting preview data, owing to its ability to optimize control inputs over a finite horizon based on predicted system behavior and external information. MPC-based formulations have been successfully applied

to several automotive applications—including adaptive cruise control, energy management, and emergency maneuvering—demonstrating robust performance in the presence of disturbances and system uncertainties [122, 123].

In the specific context of traction control, the use of preview-based MPC has gained traction as a promising approach for improving slip regulation performance under variable road conditions [124, 125]. By anticipating changes in tire-road friction or road elevation, predictive controllers can modulate the actuator torque preemptively, thus preventing excessive slip and reducing transient oscillations. This is particularly relevant for electric vehicles with centralized powertrains and open differentials, where drivetrain torsional dynamics can amplify slip errors. While several academic and industrial studies have proposed traction control strategies augmented by friction preview—such as Ford’s implementation of V2V-based surface adaptation [126], or Hyundai’s pre-emptive TCS using expected friction conditions [127]—the use of road profile previews remains comparatively unexplored. Notable exceptions concern braking applications: studies have investigated how road undulations influence ABS effectiveness and how semi-active suspension or active load control could help mitigate vertical load variations [128, 129].

3.1.1 Research contributions

In summary, to the best of the author’s knowledge, the literature lacks analyses on how the currently available information on the road profile ahead can be exploited to enhance traction control system performance. To address this identified gap, this study presents the following contributions:

- A novel TCS based on nonlinear model predictive control (NMPC), which incorporates preview information on both the future tire-road friction level and road profile within the nonlinear optimal control problem formulation.
- A sensitivity analysis of the performance improvements offered by the proposed control strategy, in comparison with state-of-the-art benchmark controllers, while accounting for variations in the electric drivetrain dynamics, model and parameter uncertainties, external disturbances, and preview information inaccuracies.

The proposed NMPC framework is evaluated through both simulations and experiments on an electric vehicle equipped with a centralized on-board powertrain architecture, which currently represents the dominant layout in the EV market. Owing to the modular structure of the prediction model, the proposed algorithm can be readily extended to alternative electric powertrain configurations, such as architectures with in-wheel motors. The focus of this work is on the control design and the potential benefits enabled by the integration of preview functionalities. Accordingly, aspects related to the generation of preview signals—such as sensing, estimation, and V2X communication infrastructure—are considered beyond the scope of this study.

3.2 Simulation and control environment

The simulation and control framework consists of the following functional blocks, shown in Figure 3.1:

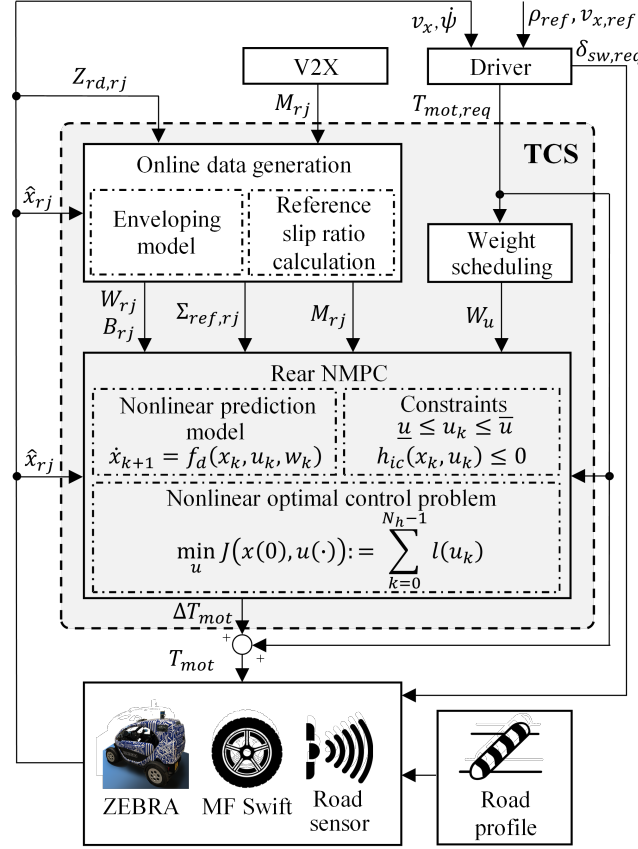


Fig. 3.1 Simplified schematic of the simulation and TCS framework.

- The human or automated driver block, which generates the torque request for the rear on-board motor, $T_{\text{mot,req}}$, and the steering wheel angle request, $\delta_{\text{sw,req}}$. Depending on the maneuver, $T_{\text{mot,req}}$ is either imposed in open-loop, or is computed through a PID cruise controller, which tracks a reference speed profile, $v_{x,\text{ref}}(t)$, where t is time, and v_x in the figure is the actual longitudinal speed. In the tests with symmetric friction and road irregularity profiles, $\delta_{\text{sw,req}}$ is imposed to be zero. In the μ -split (i.e., with asymmetric road conditions on the left and right EV sides) and cornering maneuvers, a trajectory tracking controller generates $\delta_{\text{sw,req}}$, based on the combination of feedforward and feedback contributions, where the former uses the kinematic steering condition, and the latter adopts a PID formulation on the curvature error, where the symbol ρ_{ref} in the schematic denotes the reference curvature.
- The V2X block, which outputs the vector M_{rj} of the expected tire-road friction factors along the prediction horizon, i.e., $M_{rj} = [\mu_{rj,0}, \mu_{rj,1}, \dots, \mu_{rj,k}, \dots, \mu_{rj,N_h}]$,

where $\mu_{r,j,k}$ refers to an individual value of the tire-road friction factor; the subscript r indicates that the TCS preview is implemented on the rear axle in the specific application; the subscript j , with $j = l, r$, indicates the left or right tires; and the final subscript k represents the position of the previewed value along the NMPC prediction horizon, with N_h being the number of steps of the prediction horizon.

- The TCS, which represents the novel contribution of the research, and outputs the motor torque correction, ΔT_{mot} , to be applied to the requested driver torque, i.e., the resulting reference motor torque is $T_{\text{mot,req,cr}} = T_{\text{mot,req}} + \Delta T_{\text{mot}}$.
- The nonlinear vehicle model of the case study rear-wheel-drive EV with a single on-board powertrain on the rear axle, linked to the wheels via a single-speed transmission and an open mechanical differential. The plant is implemented in Matlab-Simulink, and includes: i) the electromagnetic torque dynamics of the on-board motor through a transfer function; ii) the axle drivetrain and differential dynamics, with consideration of the torsional behavior of the half-shafts; iii) the sprung and unsprung mass dynamics in traction/braking and cornering conditions, with the nonlinearities of the suspension springs and dampers, and the longitudinal compliance characteristics related to the suspension bushings; and iv) the MF-Swift tire model [130], which is an extensively experimentally validated model for accurate tire-road contact simulation on irregular road surfaces. In the MF-Swift model, the tangential tire forces and moments are calculated by means of the Pacejka magic formula [131], which is enhanced by: a) a three-dimensional enveloping model that employs geometric filtering to capture tire behavior over road irregularities; b) a rigid ring model of the tire structure, accurately simulating tire dynamics up to 100 Hz; and c) residual stiffness and damping models between the contact patch and the rigid ring, to ensure realistic modeling of the total quasi-static tire stiffness in vertical, longitudinal, lateral, and yaw directions.

Although some of the considered simulation conditions involve vehicle cornering, for simplicity and for isolating the effect of the proposed TCS, the preliminary proof-of-concept analysis of this study neglects the presence of the stability control system based on the actuation of the friction brakes.

3.2.1 Case study vehicle and model validation

The case study electric vehicle is the prototype *Zero Emission Test Bed for Research on Autonomous Driving* (ZEBRA), developed at the University of Surrey. ZEBRA is a modified Renault Twizy, classified as an L7e rear-wheel-drive electric quadricycle, equipped with a centralized on-board electric powertrain. The drivetrain consists of a single-speed transmission, open differential, half-shafts, and constant velocity joints. The main vehicle parameters are reported in Table 3.1.

The EV is equipped with the following instrumentation:

- A set of vehicle dynamics sensors, used to measure individual wheel speeds, the vertical accelerations of the unsprung masses, and the body accelerations in the longitudinal, lateral, and vertical directions.
- Wire displacement sensors, installed to measure the vertical travel of each suspension.
- A Racelogic VBOX3i dual-antenna GPS unit, combined with a fixed base station, enabling high-precision position and velocity measurements.
- A dSPACE MicroAutoBox II unit, used as the real-time control hardware platform for rapid control prototyping of the implemented algorithms.

Table 3.1 Main vehicle parameters

Parameter	Value
Vehicle mass m_{tot}	630 [kg]
Front semi-wheelbase a	0.918 [m]
Rear semi-wheelbase b	0.768 [m]
Center of gravity height h_g	0.46 [m]
Wheel radius $R_{f/r}$	0.266 [m]
Gear ratio (motor to wheel) i_t	9.23

The nonlinear plant vehicle model, coupled with the MF-Swift tire model, was experimentally validated under two scenarios: (a) a maneuver involving a 4 cm high and 25 cm wide speed bump followed by a low-friction surface ($\mu \approx 0.3$); and (b) a skidpad test where the experimentally measured steering wheel angle, commanded by a human driver, was directly applied to the model, while a cruise controller

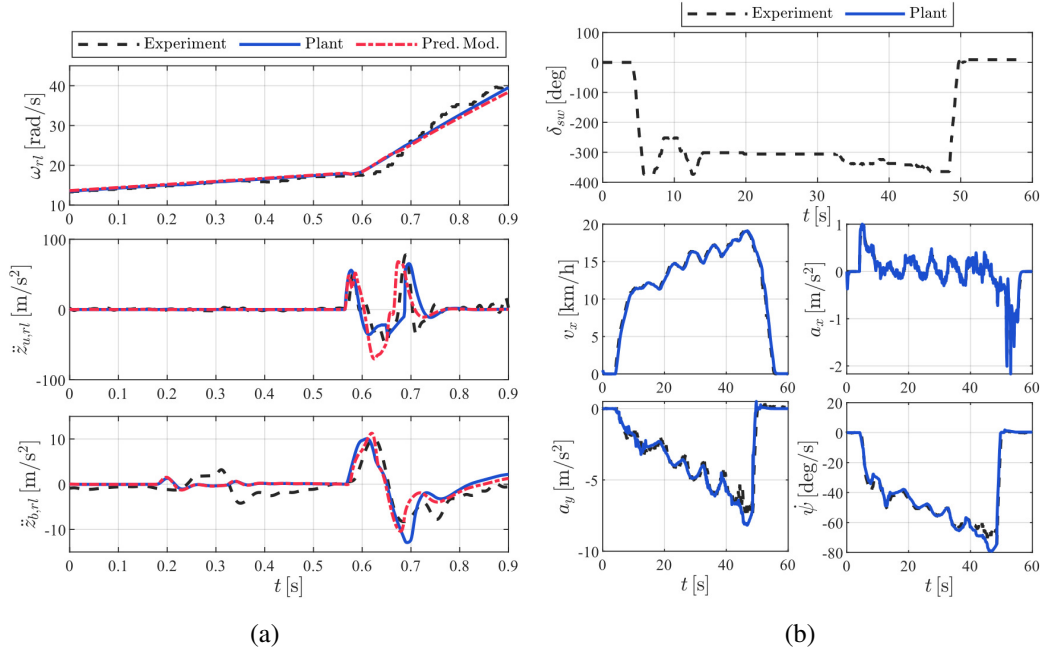


Fig. 3.2 Time profiles of: (a) the wheel speed ω_{rl} , vertical unsprung mass acceleration $\ddot{z}_{u,rl}$, and vertical vehicle body acceleration $\ddot{z}_{b,rl}$, at the rear left corner, during the speed bump test; and (b) the steering wheel angle δ_{sw} , longitudinal speed v_x , longitudinal and lateral accelerations a_x and a_y , and yaw rate $\dot{\psi}$, during the skidpad maneuver. Comparison between experimental measurements (*Experiment*), high-fidelity model results (*Plant*), and NMPC prediction model results (*Pred. Mod.*).

tracked the experimental speed profile. The results of both validation maneuvers are shown in Figure 3.2b, highlighting the good agreement between simulation and experimental data, and supporting the reliability of the high-fidelity model for control system assessment.

Additionally, the dynamic behavior of the ZEBRA powertrain was validated through tip-in tests (see Figure 3.3), which revealed a slow torque response. This behavior can be modeled using a pure time delay of approximately 100 ms followed by a first-order lag with time constant $\tau \approx 160$ ms. To evaluate the proposed traction control system in a more advanced context, the following simulation results adopt a nominal plant with faster response ($\tau = 25$ ms, no time delay).

Finally, preliminary experimental results confirm the applicability of the proposed TCS to the slower ZEBRA setup, demonstrating its robustness and effectiveness even in less ideal conditions, representative of certain segments of the EV market.

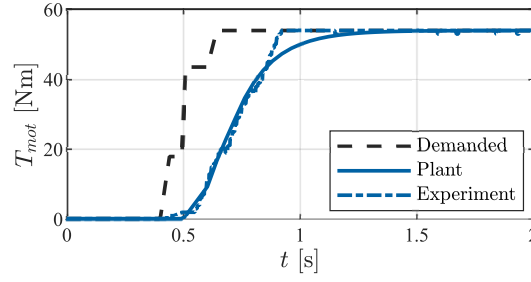


Fig. 3.3 Time profiles of the reference motor torque ('Demanded'), torque from the high-fidelity simulation model ('Plant'), and experimentally measured torque ('Experiment', from the inverter current) along a tip-in test.

3.3 Nonlinear model predictive control formulation

3.3.1 Control structure

The TCS structure shown in Figure 3.1 is implemented for the rear driving axle and includes the following components:

- **Tire Enveloping Model:** A simplified two-dimensional enveloping model of the two rear tires. The model receives as input the road profile ahead along the prediction horizon, defined as:

$$\mathbf{Z}_{rd,rj} = [z_{rd,rj,0}, z_{rd,rj,1}, \dots, z_{rd,rj,k}, \dots, z_{rd,rj,N_h}],$$

where $z_{rd,rj,k}$ denotes the individual vertical displacement, generated from a road elevation map. This map may be provided by a road scanning sensor; however, the scanning and information generation methodology is beyond the scope of this research. The outputs of the enveloping model are:

- the effective road height vector:

$$\mathbf{W}_{rj} = [w_{rj,0}, w_{rj,1}, \dots, w_{rj,k}, \dots, w_{rj,N_h}],$$

- and the effective slope vector:

$$\mathbf{r}_{rj} = [\beta_{rj,0}, \beta_{rj,1}, \dots, \beta_{rj,k}, \dots, \beta_{rj,N_h}],$$

- **Slip Ratio Threshold Generator:** This module computes the vector of slip ratio bounds for the rear-left and rear-right tires:

$$\Sigma_{\text{ref},rj} = [\sigma_{\text{ref},rj,0}, \sigma_{\text{ref},rj,1}, \dots, \sigma_{\text{ref},rj,k}, \dots, \sigma_{\text{ref},rj,N_h}],$$

using two-dimensional look-up tables, as a function of the expected tire-road friction factors μ_{rj} in the vector rj .

- **Cost Function Weight Generator:** This block defines the NMPC cost function weights W_u , which are kept constant across the maneuvers in this preliminary study.
- **Nonlinear Model Predictive Control (NMPC):** The implicit NMPC algorithm for the rear on-board centralized powertrain computes the online solution of the nonlinear optimal control problem in the form of a torque reduction ΔT_{mot} , based on a prediction model of the EV rear axle dynamics and the defined external inputs.

3.3.2 Enveloping model

Many relevant ride events, affecting both vertical and longitudinal vehicle dynamics, are induced by road irregularities with dimensions comparable to the tire-road contact patch. In such cases, the wheel enveloping effect is non-negligible, and raw road profile data from scanning sensors cannot be directly used in the simplified tire models of the NMPC algorithm.

To address this, a tire enveloping model is required to process the measured road profile and generate an effective profile suitable for control purposes. In the proposed control architecture, the tandem enveloping model with elliptical cams by Schmeitz [132, 133] is adopted. This model provides a computationally efficient estimation of the effective road height w and slope β_y , without requiring time-domain integration.

The model is calibrated using the high-fidelity MF-Swift tire model integrated in the nonlinear vehicle simulator. As shown in Figure 3.4, the outputs of the two-cam model closely match those of the MF-Swift model across representative road profiles (speed bump and ISO class B/C surfaces), validating its use for control. Moreover, significant differences between the raw profile ('Ref') and the effective

ones ('Env. Mod.' and 'MF-Swift') confirm that, under these conditions, direct use of unprocessed road data would compromise the NMPC prediction accuracy.

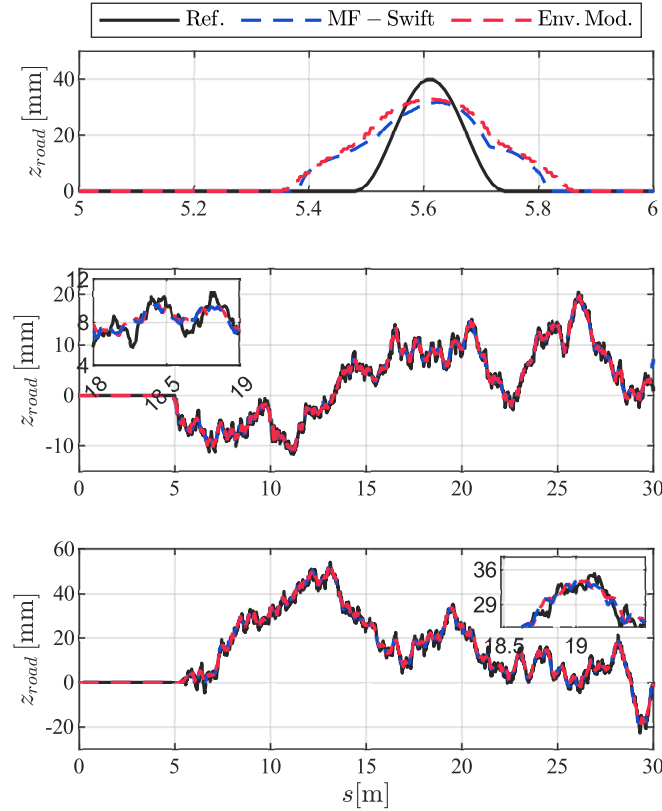


Fig. 3.4 Comparison of the effective road profiles generated by the MF-Swift tire model ('MF-Swift') and the tandem enveloping model ('Env. Mod.'), starting from raw road profile data ('Ref') in terms of vertical displacement, along (from top to bottom) a 4 cm high and 25 cm wide speed bump, an ISO class B road profile, and an ISO class C road profile, where s is the traveled distance.

3.3.3 Prediction model

The prediction model used within the NMPC algorithm includes the tire and wheel dynamics of each rear corner, the vertical and longitudinal dynamics of the corresponding unsprung masses, the vertical dynamics of the rear sprung mass, and the longitudinal dynamics of the overall sprung mass. Since the focus is on the rear driving axle, the vertical and longitudinal dynamics of the front unsprung masses are

neglected. The resulting mechanical system has eight degrees of freedom, complemented by a differential equation describing the torque dynamics of the rear electric drive, which distributes torque equally between the left and right wheels.

As shown in Figure 3.5 (left side view), m_{app} represents the apparent mass of the vehicle, including the inertia of the front wheels and other relevant rotating parts. The inertia of the rear rotating components, such as the wheels and motor rotor, is directly included in the torque balance of the rear wheels. In contrast, m_{app} accounts for the front wheel inertia, which contributes to the overall vehicle inertia but is not detailed in the model. This simplification, along with the omission of torsional and backlash dynamics (considered negligible for the specific EV) allows for an efficient prediction while capturing the correct overall inertia.

The unsprung mass is modeled with a central non-rotating body (upright, suspension arms, brake caliper) and an outer rotating part (wheel rim and brake disc). The suspension is represented by vertical stiffness and nonlinear damping between sprung and unsprung masses. Longitudinal compliance at each rear corner is modeled through springs and dampers with stiffness $k_{x,r}$ and damping $c_{x,r}$.

Road irregularities affect both vertical and longitudinal sprung mass dynamics. The tire structure is modeled via two spring-damper systems: a radial one with stiffness $k_{r,r}$ and damping $c_{r,r}$, and a tangential one with stiffness $k_{t,r}$ and damping $c_{t,r}$. These act on the non-rotating part of the unsprung mass and are assumed to contact the road through a frictionless roller. The longitudinal tire force from slip is applied to the rotating part and transmitted to the non-rotating part via the bearing system shown in Figure 3.5.

The proposed formulation achieves sufficient accuracy while significantly simplifying the model compared to the MF-Swift tire model. It can also be adapted to other EV architectures with centralized on-board motors, such as front-wheel-drive and rear-wheel-drive layouts, and extended to include torsional drivetrain dynamics or direct-drive in-wheel motors.

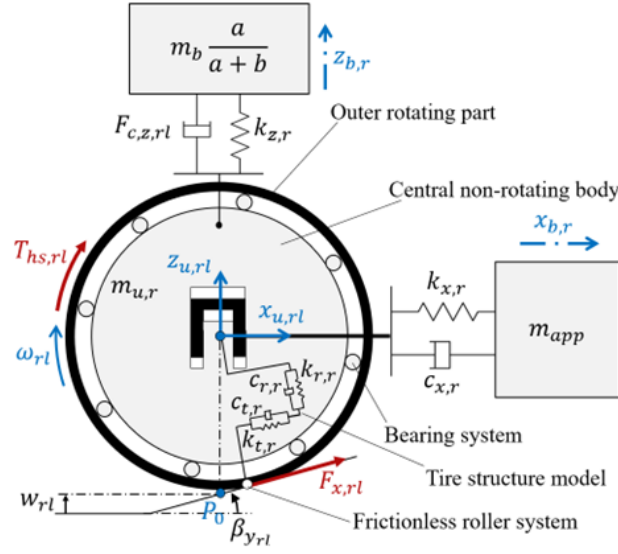


Fig. 3.5 Lateral view of the left side of the NMPC prediction model.

The prediction model dynamics of the considered rear-wheel drive EV are described by the following equations:

Electromagnetic torque dynamics of the central rear motor:

$$\dot{T}_{\text{mot}} = [T_{\text{mot,req,cr}} - T_{\text{mot}}] \frac{1}{\tau} \quad (3.1)$$

where T_{mot} is the actual electromagnetic motor torque, and τ is the respective time constant.

Vertical force balance of the rear sprung mass:

$$\ddot{z}_{b,r} = \left\{ \sum_{j=l,r} [-F_{k,z,rj} - F_{c,z,rj}] + F_{z,b,r} \right\} \frac{1}{m_b} \cdot \frac{a+b}{a} \quad (3.2)$$

where m_b is the total sprung mass of the vehicle; $F_{k,z,rj}$ and $F_{c,z,rj}$ are the vertical suspension forces, associated with the spring and shock absorber of each rear corner; and $F_{z,b,r}$ is the rear longitudinal load transfer contribution going through the deformable suspension components.

More specifically:

$$F_{k,z,rj} = k_{z,r} (z_{b,rj} - z_{u,rj}) \quad (3.3)$$

where $k_{z,r}$ is the vertical suspension stiffness, and $z_{u,rj}$ is the vertical displacement of the unsprung mass of the considered rear corner.

Vertical damping force is calculated with a continuous nonlinear function:

$$F_{c,z,rj} = a_{1,r} + b_{1,r} \cdot \tan^{-1} (c_{1,r}(\dot{z}_{b,rj} - \dot{z}_{u,rj}) + d_{1,r}) + b_{2,r} \cdot \tan^{-1} (c_{2,r}(\dot{z}_{b,rj} - \dot{z}_{u,rj}) + d_{2,r}) \quad (3.4)$$

where $a_{1,r}$, $b_{1/2,r}$, $c_{1/2,r}$, and $d_{1/2,r}$ are constant coefficients.

The rear longitudinal load transfer contribution is given by:

$$F_{z,b,r} = m_{\text{tot}} \ddot{x}_b \frac{h_g}{a+b} - \sum_{j=l,r} F_{z,\text{ap},rj} \quad (3.5)$$

where h_g is the center of gravity height, m_{tot} is the total vehicle mass, and $F_{z,\text{ap},rj}$ is the longitudinal load transfer component through rigid suspension links due to suspension anti-properties.

The anti-properties contribution is:

$$F_{z,\text{ap},rj} = \frac{1}{2} m_{\text{tot}} \ddot{x}_b \tan \varphi_{rj} \quad (3.6)$$

where φ_{rj} is the effective angle of the equivalent trailing arm representing the suspension geometry.

Vertical force balance of the unsprung mass at each rear corner:

$$\ddot{z}_{u,rj} = [F_{c,z,rj} + F_{k,z,rj} + F_{r,z,rj} - F_{t,z,rj} + F_{x,z,rj} - F_{z,\text{ap},rj}] \frac{1}{m_{u,r}} \quad (3.7)$$

where $m_{u,r}$ is the unsprung mass; $F_{r,z,rj}$ and $F_{t,z,rj}$ are the vertical components of the tire radial and tangential forces:

$$F_{r,rj} = k_{r,r}(w_{rj} - z_{u,rj}) \cos \beta_{y,rj} + c_{r,r}(\dot{w}_{rj} - \dot{z}_{u,rj}) \cos \beta_{y,rj} \quad (3.8)$$

$$F_{t,rj} = k_{t,r}(w_{rj} - z_{u,rj}) \sin \beta_{y,rj} + c_{t,r}(\dot{w}_{rj} - \dot{z}_{u,rj}) \sin \beta_{y,rj} \quad (3.9)$$

under the assumption that the time derivative of $\beta_{y,rj}$ is negligible.

$F_{x,z,rj}$ is the vertical component of the longitudinal tire force $F_{x,rj}$, obtained via the Pacejka model under zero slip angle.

Longitudinal force balance of the vehicle sprung mass:

$$\ddot{x}_b = \left\{ \sum_{j=l,r} [-F_{k,x,rj} - F_{c,x,rj}] - F_{\text{drag}} - F_{\text{roll},f} \right\} \frac{1}{m_{\text{app}}} \quad (3.10)$$

where the traction force is transmitted to the sprung mass through the suspension bushings, whose longitudinal force components are $F_{k,x,rj}$ and $F_{c,x,rj}$:

$$F_{k,x,rj} = k_{x,r}(x_{b,rj} - x_{u,rj}) \quad (3.11)$$

$$F_{c,x,rj} = c_{x,r}(\dot{x}_{b,rj} - \dot{x}_{u,rj}) \quad (3.12)$$

The aerodynamic drag is:

$$F_{\text{drag}} = \frac{1}{2} \rho_{\text{air}} C_d A_{\text{car}} \dot{x}_b^2 \quad (3.13)$$

where ρ_{air} is the air density, C_d is the aerodynamic drag coefficient, and A_{car} is the frontal area of the EV. The front axle rolling resistance is:

$$F_{\text{roll},f} = f_{\text{roll},f} m_{\text{tot}} \frac{b}{a+b} g \quad (3.14)$$

Where the rolling resistance coefficient is expressed as:

$$f_{\text{roll}} = f_0 + f_2 \dot{x}_b^2 \quad (3.15)$$

with f_0 and f_2 being constant coefficients. The apparent mass m_{app} is defined as:

$$m_{\text{app}} = m_b + 2m_{u,f} + \frac{2I_{y,f}}{R_f^2} \quad (3.16)$$

where $m_{u,f}$ is the individual front unsprung mass, $I_{y,f}$ includes the mass moments of inertia of the rotating parts of the front corners, and R_f is the rolling radius of the front tires.

Longitudinal dynamics of the rear unsprung mass:

$$\ddot{x}_{u,rj} = [F_{c,x,rj} + F_{k,x,rj} - F_{r,x,rj} - F_{t,x,rj} + F_{x,x,rj}] \frac{1}{m_{u,r}} \quad (3.17)$$

where $F_{r,x,rj}$, $F_{t,x,rj}$, and $F_{x,x,rj}$ are the longitudinal components of $F_{r,rj}$, $F_{t,rj}$, and $F_{x,rj}$.

Rear wheel rotational dynamics:

$$\dot{\omega}_{rj} = [T_{hs,rj} - F_{x,rj}\hat{R}_{lad,r} - M_{y,rj}] \frac{1}{I_{y,r}} \quad (3.18)$$

where $\dot{\omega}_{rj}$ is the angular wheel acceleration, $M_{y,rj}$ is the rolling resistance moment of the specific tire and drivetrain, $\hat{R}_{lad,r}$ is the laden radius of the rear tires, and $T_{hs,rj}$ is the individual half-shaft torque:

$$T_{hs,rj} = \frac{1}{2} i_t \eta_t T_{mot} \quad (3.19)$$

The NMPC prediction model (3.1)–(3.19) is rearranged in discrete nonlinear state-space form:

$$x_{k+1} = f_d(x_k, u_k, p_k) \quad (3.20)$$

where f_d indicates the corresponding discrete nonlinear function, and x_k , u_k , and p_k are the state, control input, and parameter vectors, with the subscript k indicating a generic time step along the prediction horizon. x_k is defined as:

$$x_k = \begin{bmatrix} \dot{z}_{b,r} & z_{b,r} & \dot{z}_{b,rl} - \dot{z}_{u,rl} & z_{b,rl} - z_{u,rl} & \dot{z}_{b,rr} - \dot{z}_{u,rr} & z_{b,rr} - z_{u,rr} & \dot{x}_b & x_b \\ \dot{x}_{u,rl} & x_{u,rl} & \dot{x}_{u,rr} & x_{u,rr} & \omega_{rl} & \omega_{rr} & T_{mot} \end{bmatrix}^T \quad (3.21)$$

Input vector is given by:

$$u_k = \begin{bmatrix} \Delta T_{mot} & \varepsilon_{\sigma_{rl}} & \varepsilon_{\sigma_{rr}} \end{bmatrix} \quad (3.22)$$

where the actual control input applied to the plant, ΔT_{mot} , is complemented by the virtual control inputs represented by the slack variables, $\varepsilon_{\sigma_{rl/rr}}$, which are used to impose the soft constraints on the longitudinal tire slip.

The parameters vector is:

$$p_k = \begin{bmatrix} w_{rl} & \beta_{y,rl} & w_{rr} & \beta_{y,rr} & \mu_{rl} & \sigma_{ref,rl} & \mu_{rr} & \sigma_{ref,rr} & T_{mot,req} \end{bmatrix}^T \quad (3.23)$$

where, in NMPC implementations with road preview, w_{rj} , $\beta_{y,rj}$, μ_{rj} , and $\sigma_{ref,rj}$ vary along the prediction horizon $H_p = \sum_{k=0}^{N_h-1} T_{s,k}$, with $T_{s,k}$ being the controller

sampling time at step k , and N_h the number of prediction steps. The preview parameters at step k are computed based on the expected wheel travel, given by $x_{u,rj,k} = x_{u,rj,0} + \dot{x}_{u,rj,0} \sum_{n=0}^k T_{s,n}$ assuming constant speed over the short horizon H_p .

3.3.4 Nonlinear optimal control problem

At each time step, the nonlinear optimal control problem formulation aims to minimize the cost function J , according to:

$$\begin{aligned}
 \min_u \quad & J(x(0), u(\cdot)) := \sum_{k=0}^{N_h-1} \ell(u_k) \\
 \text{s.t.} \quad & x_0 = x_{\text{in}} \\
 & x_{k+1} = f_d(x_k, u_k, p_k) \\
 & \underline{u} \leq u_k \leq \bar{u} \\
 & h_{\text{ic}}(x_k, u_k) \leq 0 \\
 & u(\cdot) : [0, N_h - 1]
 \end{aligned} \tag{3.24}$$

where $u(\cdot) = [u_0 \ u_1 \ \dots \ u_{N_h}]^T$ is the sequence of augmented control input vectors along H_p , which in this case coincides with the control horizon; x_{in} is the initial value of the state vector; $\underline{u}$ and $\bar{u}$ are vectors containing the lower and upper bounds of the control input u ; h_{ic} is the inequality constraint function; and $\ell(u_k)$ is the stage cost, which is given by: The stage cost $\ell(u_k)$ is defined as:

$$\ell(u_k) = W_{u, \Delta T_{\text{mot}}} \Delta T_{\text{mot},k}^2 + \sum_{j=l,r} W_{u, \varepsilon_{\sigma_r}} \varepsilon_{\sigma_{rj,k}}^2 \tag{3.25}$$

where $W_{u, \Delta T_{\text{mot}}}$ and $W_{u, \varepsilon_{\sigma_r}}$ are weights, respectively penalizing the TCS-induced torque reduction and the slack variables.

The control input and inequality constraints are:

$$\text{Lb}_{T_{\text{mot}}} \leq T_{\text{mot},k} + \Delta T_{\text{mot},k} \leq \text{Ub}_{T_{\text{mot}}} \tag{3.26}$$

$$\sigma_{rj,k} + \varepsilon_{\sigma_{rj,k}} \leq \sigma_{\text{ref},rj,k} \tag{3.27}$$

$$\varepsilon_{\sigma_{rj,k}} \geq 0 \tag{3.28}$$

where $\text{Lb}_{T_{\text{mot}}}$ and $\text{Ub}_{T_{\text{mot}}}$ are the lower and upper boundaries of the motor torque, implemented as hard constraints; and the last two inequalities are soft constraints on the violation of the longitudinal slip ratio threshold, $\sigma_{\text{ref},rj,k}$, generated from predetermined lookup tables. These thresholds are used to keep the longitudinal tire slip ratio $\sigma_{rj,k}$ close to the value corresponding to the maximum traction force for each friction factor $\mu_{rj,k}$. The slip ratio $\sigma_{rj,k}$ is expressed as:

$$\sigma_{rj,k} = 1 - \frac{v_{x,u,rj,k}}{\omega_{rj,k} R_r} \quad (3.29)$$

The ACADO toolkit, which offers a robust platform for NMPC development [134], is employed to implement the controllers. The selected solver settings include the qpOASES optimization algorithm, the fourth-order Runge-Kutta integrator, and the multiple shooting discretization method. In the proposed formulation, the calibration of the cost function weights is straightforward, since the main control objective is the imposition of a soft constraint through a slack variable, rather than the continuous tracking of a reference profile. Therefore, a brute force procedure was used to achieve constant calibrations of the weights across the simulated maneuvers, controller variants, and settings (e.g., in terms of H_p and $T_{(s,k)}$), as detailed in the following sections.

3.4 Performance assessment

The controller performance is evaluated along the following test scenarios:

1. **Speed bump test**, consisting of a 4 cm high and 25 cm wide speed bump, followed by a low-friction patch with a tire-road friction coefficient $\mu \approx 0.3$. This set-up is also replicated in the experimental tests.
2. **Irregular road profile tests**, corresponding to the sections shown in Fig. 4 of standardized ISO class B and class C roads, with variable tire-road friction levels. Specifically, three friction jumps are introduced: the first from $\mu = 1$ to 0.4, the second from 0.4 to 1, and the third from 1 to 0.3.
3. **Straight-line speed bump test in μ -split conditions**, performed at 30 km/h. It uses the same road profile as in case (1), followed by a low-friction patch

applied only to the left wheels, with $\mu \approx 0.3$. The vehicle is kept on an approximately straight-line trajectory via the feedforward and feedback steering controller for path tracking.

In all the scenarios, the torque demand is kept at the maximum level (57 Nm) that is allowed by the ZEBRA powertrain.

The following set of key performance indicators (KPIs) is used to evaluate the TCS performance:

- The peak value, σ_{peak} , of the rear longitudinal tire slips, along the considered test:

$$\sigma_{\text{peak}} = \max(\max(\sigma_{rl}), \max(\sigma_{rr})) \quad (3.30)$$

where the notation $\max(\cdot)$ indicates the maximum value along a time series of data.

- The integral of the longitudinal tire slip violation, $\hat{e}_{\sigma}$, averaged over time:

$$\hat{e}_{\sigma} = \frac{1}{t_{\text{fin}} - t_{\text{in}}} \int_{t_{\text{in}}}^{t_{\text{fin}}} [e_{\sigma_{rl}} + e_{\sigma_{rr}}] dt \quad (3.31)$$

where t_{in} and t_{fin} are the initial and final times of the relevant part of the test, e.g., the one in which the rear wheels are on the low-friction surface in the speed bump test, and the road section with geometric irregularities in the ISO road profile tests; and $e_{\sigma_{rl}}$ and $e_{\sigma_{rr}}$ are the tire slip constraint violations, which define the extent by which the actual tire slip exceeds the threshold value in traction conditions:

$$e_{\sigma_{rj}} = \text{sat}(\sigma_{rj} - \sigma_{\text{ref},rj})_0^{\infty} \quad (3.32)$$

- The speed at the end of the maneuver, $v_{f,\text{in}}$, which is an indicator of the resulting longitudinal acceleration performance.

For the maneuvers involving μ -split conditions, also the following indicators are considered, to assess the level of excitation of the lateral vehicle dynamics induced by the tire-road friction asymmetry:

- The maximum absolute value of the lateral acceleration, $|a_y|_{\text{max}}$, computed in the relevant part of the test, i.e., during the μ -split-provoked transient.

- The integral of the absolute value of the steering angle averaged over time:

$$\text{IACA}_\delta = \frac{1}{t_{\text{fin}} - t_{\text{in}}} \int_{t_{\text{in}}}^{t_{\text{fin}}} |\delta| dt \quad (3.33)$$

3.5 Simulation results

The simulations presented in this section rely on the experimentally validated non-linear vehicle model described in Section 3.2.1. The performance of the proposed $\text{NMPC}^{\text{full prev.}}$ configuration, which leverages preview information on both the road profile and the friction coefficient, is compared against: $\text{NMPC}^{\mu \text{ prev.}}$, which excludes the road profile preview; $\text{NMPC}^{\text{w/o prev.}}$, which does not use any preview information; a TCS based on the integral sliding mode control (SMC) formulation from [114], originally developed for braking and adapted here for traction conditions, with a 1 ms sampling time unless otherwise specified; and the passive vehicle, i.e., without any TCS.

3.5.1 Sensitivity analysis on sampling time and prediction horizon

This section investigates the optimal controller settings for $\text{NMPC}^{\text{full prev.}}$, focusing on the sampling time T_s and prediction horizon H_p , evaluated through the speed bump test. The prediction model is discretized with $T_d = 1$ ms, and the same cost function weights are used across all configurations.

Figure 3.6 reports the normalized computational time $\bar{T}_c$, plotted against the slip control KPIs σ_{peak} and $\hat{e}_\sigma$. For a given H_p , increasing T_s reduces the computational load, with a sharp drop from 1 ms to 5 ms and moderate gains up to 10 ms. However, larger T_s can worsen control performance. Conversely, increasing H_p improves slip control, as it allows the NMPC to anticipate and counteract the effect of previewed road irregularities and drivetrain delays. Beyond $H_p = 90$ ms, performance gains saturate or slightly degrade, while computational cost continues to rise.

For the simulated EV with torque time constant $\tau = 25$ ms, the setting $T_s = 10$ ms and $H_p = 90$ ms offers a favorable trade-off between performance and computational

efficiency. Longer horizons may be required for slower powertrains (see Section 3.5.3).

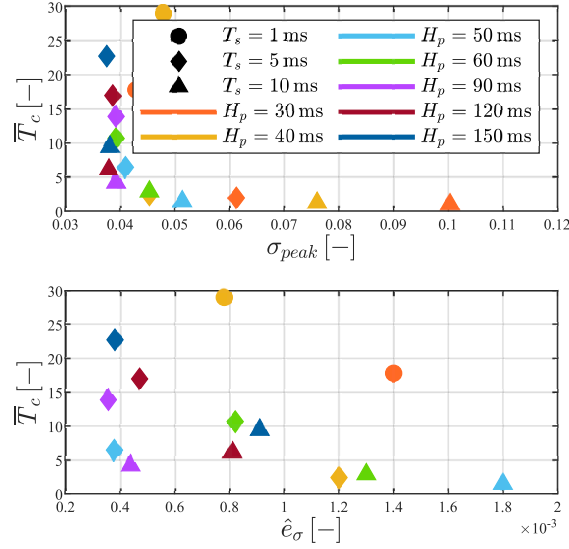


Fig. 3.6 $\bar{T}_c$ as a function of σ_{peak} and $\hat{e}_\sigma$, for different values of T_s and H_p , for NMPC^{full prev.}.

3.5.2 Speed bump test results

For the speed bump test, Figure 3.7 shows the evolution of the longitudinal slip ratio, the vehicle speed, and the wheel torque versus the traveled distance s for the passive EV and the same vehicle equipped with traction controllers: NMPC^{full prev.}, NMPC ^{μ prev.}, NMPC^{w/o prev.}, and sliding mode control. Two NMPC settings are considered: (a) $T_s = 10$ ms, $H_p = 90$ ms, identified as optimal for NMPC^{full prev.}; and (b) $T_s = 5$ ms, $H_p = 50$ ms, sub-optimal for full preview but potentially effective for other configurations. Given the symmetry of the selected road profile, the figure plots the slip ratio only for the rear left corner.

The cost function weights are kept constant for both setups. Thanks to the bump preview and longer horizon, NMPC^{full prev.} significantly limits slip violations, with $\sigma_{peak} \approx 0.032$ (a) and 0.041 (b), while maintaining a competitive final speed, due to the pre-emptive torque modulation. In contrast, NMPC ^{μ prev.}, NMPC^{w/o prev.}, and SMC are less effective: σ_{peak} can reach 0.11–0.17 (a) and 0.08–0.13 (b), highlighting the greater importance of a longer H_p when preview information is incomplete.

SMC slightly outperforms $\text{NMPC}^{\text{w/o prev.}}$ in slip mitigation, but remains inferior to $\text{NMPC}^{\text{full prev.}}$, and introduces torque chattering at approximately 15 Hz, which can affect ride comfort.

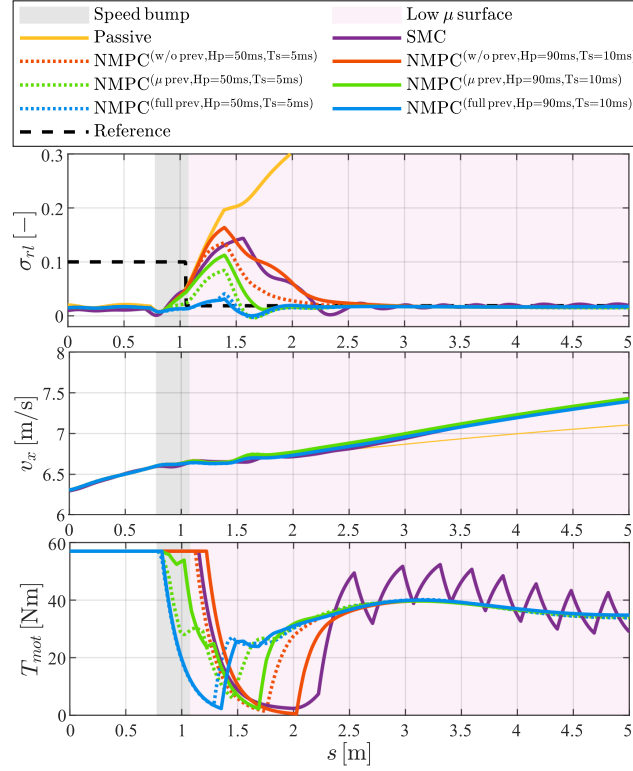


Fig. 3.7 Performance comparison in terms of σ_{sl} , v_x , and T_{mot} profiles as a function of s , during the speed bump test, simulated with the passive EV, and the same EV with SMC, and two $\text{NMPC}^{\text{full prev.}}$, $\text{NMPC}^{\mu \text{ prev.}}$, and $\text{NMPC}^{\text{w/o prev.}}$ configurations: $T_s = 10$ ms and $H_p = 90$ ms (continuous lines), and $T_s = 5$ ms and $H_p = 50$ ms (dashed lines). Here and in the remainder, grey areas indicate the speed bump location; pink regions highlight low-friction surfaces; and the dashed line represents the longitudinal slip threshold profile.

3.5.3 Sensitivity to actuation dynamics

This analysis evaluates the influence of different powertrain torque time constants, $\tau = 60, 90$, and 120 ms, on TCS performance during the speed bump test. Two NMPC settings are considered, both with $T_s = 10$ ms and $H_p = 90$ or 150 ms. As shown in Figure 3.8, increasing τ leads to a general degradation in performance, as indicated by higher values of σ_{peak} and $\hat{e}_\sigma$.

Consistent with the findings, $\text{NMPC}^{\text{full prev.}}$ benefits from a longer horizon: with $H_p = 150$ ms, it outperforms the same configuration with $H_p = 90$ ms. Conversely, $\text{NMPC}^{\mu \text{ prev.}}$ and $\text{NMPC}^{\text{w/o prev.}}$ show better results with shorter horizons.

For $\tau = 60$ ms, $\text{NMPC}^{\text{full prev.}}$ with $H_p = 90$ ms reduces σ_{peak} and $\hat{e}_{\sigma}$ by 65% and 94% compared to $\text{NMPC}^{\text{w/o prev.}}$, and by 50% and 79% compared to $\text{NMPC}^{\mu \text{ prev.}}$. These reductions further improve with $H_p = 150$ ms, reaching up to 76% and 97% (vs. $\text{NMPC}^{\text{w/o prev.}}$), and 65% and 95% (vs. $\text{NMPC}^{\mu \text{ prev.}}$).

For slower dynamics ($\tau = 120$ ms), the benefit of a longer prediction horizon becomes more pronounced. $\text{NMPC}^{\text{full prev.}}$ with $H_p = 150$ ms achieves a 61% and 95% reduction in σ_{peak} and $\hat{e}_{\sigma}$ vs. $\text{NMPC}^{\text{w/o prev.}}$, and 42% and 83% vs. $\text{NMPC}^{\mu \text{ prev.}}$, corresponding to an additional 8% and 21% improvement over the $H_p = 90$ ms case.

Interestingly, SMC is more sensitive to increasing τ than $\text{NMPC}^{\text{w/o prev.}}$, highlighting the advantage of predictive control when facing slow actuator dynamics. Despite the deliberately conservative values of τ , $\text{NMPC}^{\text{full prev.}}$ consistently delivers superior and robust performance, supporting its applicability across a broad range of electric powertrain systems.

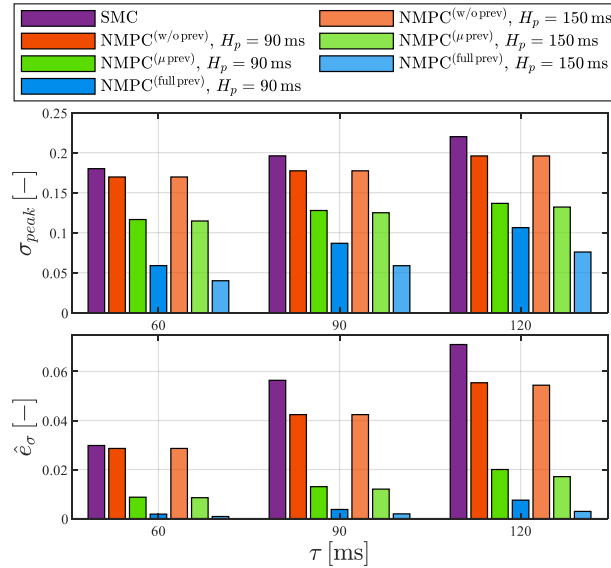


Fig. 3.8 σ_{peak} and $\hat{e}_{\sigma}$ for the rear left corner, for different values of τ and H_p , for the NMPC configurations and SMC along the considered speed bump test.

3.5.4 Controller evaluation for different symmetric road and friction profiles

Figures 3.9 show the profiles of key variables over the ISO class B and C road sections [135] with varying friction, while the corresponding KPIs are reported in Table 3.2. For SMC, two variants are evaluated: ‘SMC – 1 ms’ and ‘SMC – 10 ms’, with the latter aligned with the NMPC sampling time.

In the passive case, traction is lost on low-friction patches, causing speed reduction. However, upon returning to high-friction conditions (e.g., $s \approx 11$ m), the passive vehicle re-accelerates rapidly due to the high wheel speed, unlike the TCS cases.

At the first μ drop ($s \approx 6$ m), $\text{NMPC}^{\text{w/o prev.}}$ and $\text{NMPC}^{\mu \text{ prev.}}$ yield similar slip peaks ($\sigma_{\text{peak}} \approx 0.05$), as friction preview alone is insufficient to anticipate constraint violations when the slip threshold is relatively high.

SMC – 1 ms better compensates slip on low-friction surfaces (e.g., $s > 20$ m), reducing $\hat{e}_{\sigma}$ by 40–51% vs. $\text{NMPC}^{\text{w/o prev.}}$ and 49–52% vs. $\text{NMPC}^{\mu \text{ prev.}}$. However, it remains less effective during abrupt μ transitions, and SMC – 10 ms shows a clear overall performance decline.

With full preview, $\text{NMPC}^{\text{full prev.}}$ anticipates load variations due to road irregularities and adjusts T_{mot} pre-emptively to prevent constraint violations. In the most challenging conditions (e.g., $\mu = 0.3$ at $s \approx 16$ m or the irregular class C profile), it ensures minimal slip threshold violations and higher exit speeds than the passive EV. Table 3.2 confirms its superior slip control, halving σ_{peak} and reducing $\hat{e}_{\sigma}$ by over one order of magnitude compared to all other controllers, especially on the more demanding class C road.

3.5.5 Speed bump tests in μ -split conditions

This analysis evaluates TCS performance under asymmetric friction conditions between the left and right tires, where the vehicle is subjected to lateral and yaw motions.

In the straight-line acceleration scenario of Figure 3.10, the passive vehicle exhibits significant lateral and yaw dynamics due to the rear-left wheel encountering

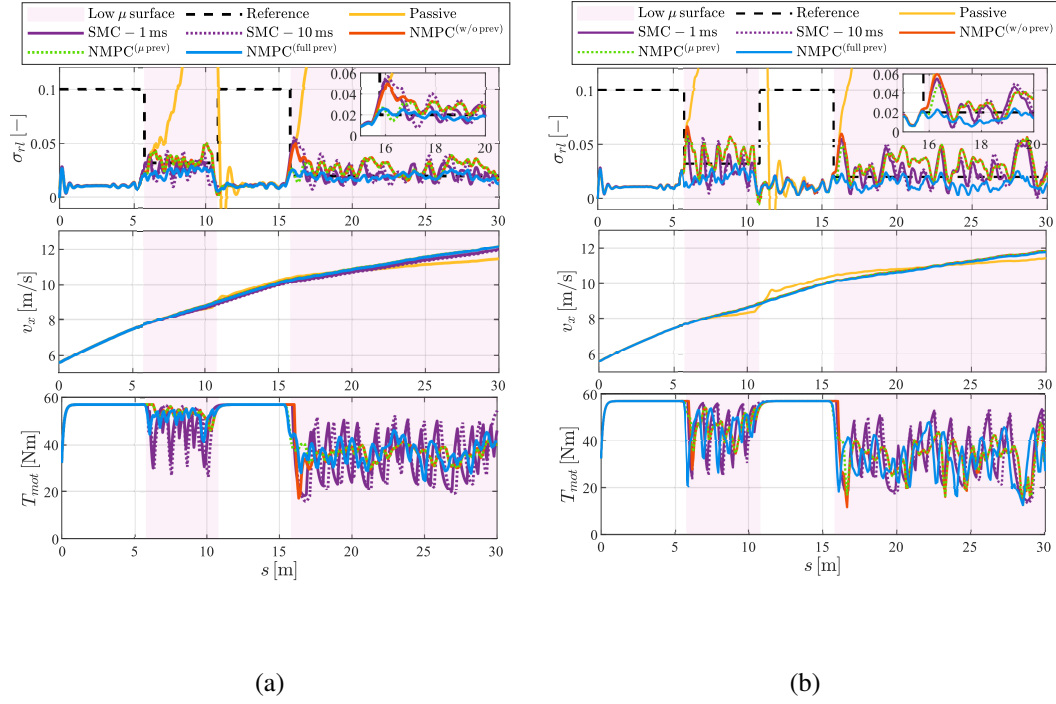


Fig. 3.9 Performance comparison of the considered SMCs and NMPCs in terms of σ_{rl} , v_x , and T_{mot} profiles, along sections of (a) an ISO class B road and (b) an ISO class C road, with varying friction levels.

the low-friction surface after the bump, resulting in $|a_y|_{\max} = 2.9 \text{ m/s}^2$ and requiring substantial corrective steering.

SMC, $\text{NMPC}^{w/o \text{ prev.}}$, and $\text{NMPC}^{\mu \text{ prev.}}$ offer only marginal improvements in reducing the initial slip peak and lateral oscillations. In contrast, $\text{NMPC}^{\text{full prev.}}$, via anticipatory torque reduction, decreases σ_{peak} by 60% and 56% compared to $\text{NMPC}^{w/o \text{ prev.}}$ and SMC, respectively. Moreover, lateral instability are significantly mitigated, with steering effort IACA_{δ} reductions of 82% and 66% relative to $\text{NMPC}^{w/o \text{ prev.}}$ and $\text{NMPC}^{\mu \text{ prev.}}$.

Table 3.2 Comparison of σ_{peak} , $\hat{e}_{\sigma}$, and v_{fin} for SMC and NMPC configurations on ISO class B and class C roads.

Road	Controller	σ_{peak} [-]	$\hat{e}_{\sigma}$ [-]	v_{fin} [m/s]
ISO class B	SMC-1 ms	0.053	0.0021	11.40
	SMC-10 ms	0.061	0.0031	11.36
	NMPC ^{w/o prev.}	0.050	0.0043	11.57
	NMPC ^{μ prev.}	0.050	0.0035	11.58
	NMPC ^{full prev.}	0.029	0.00037	11.56
ISO class C	SMC-1 ms	0.062	0.0036	11.27
	SMC-10 ms	0.062	0.0040	11.26
	NMPC ^{w/o prev.}	0.067	0.0076	11.25
	NMPC ^{μ prev.}	0.057	0.0071	11.28
	NMPC ^{full prev.}	0.032	0.00012	11.23

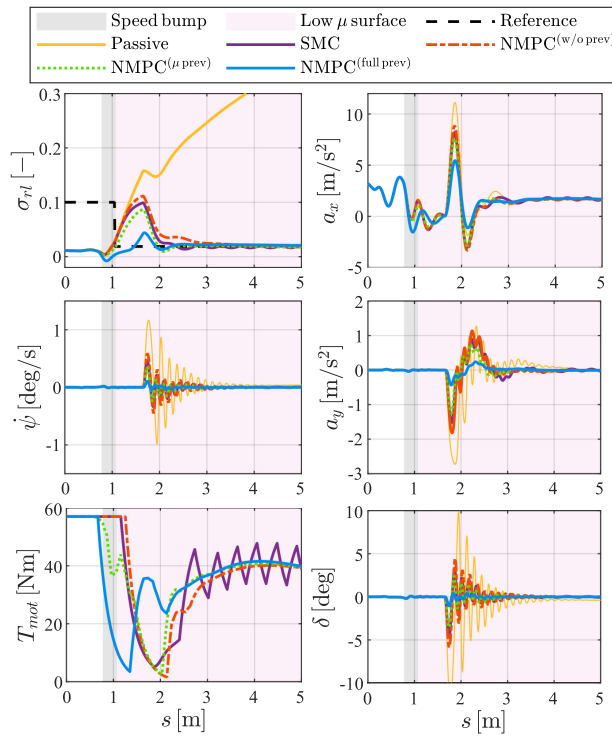
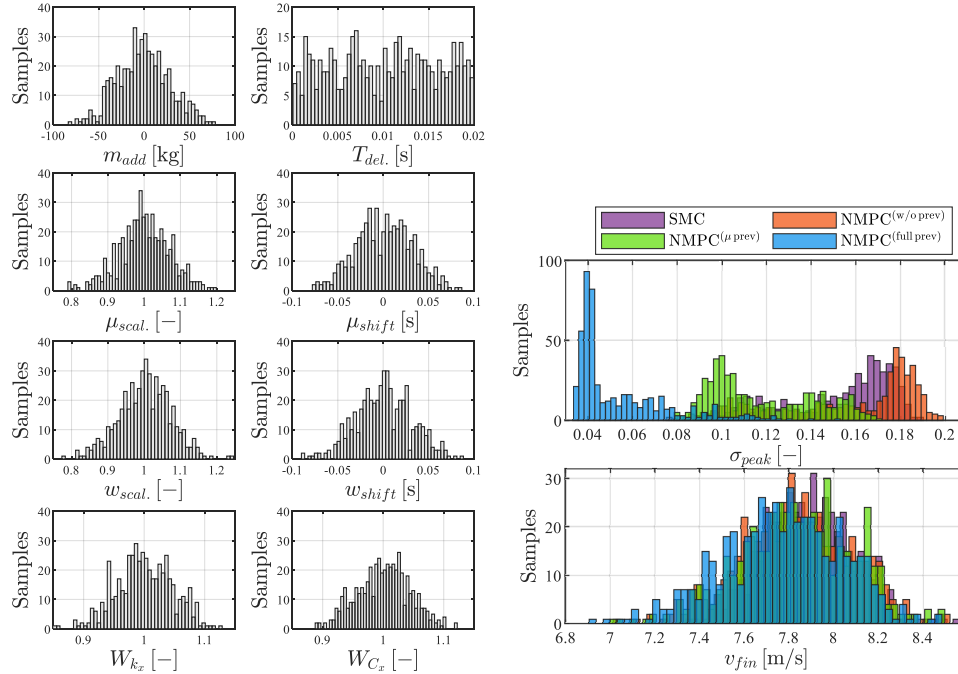


Fig. 3.10 Performance comparison in terms of σ_{rl} , a_x , ψ , a_y , T_{mot} , and δ profiles as a function of s , for the considered speed bump test followed by a μ -split surface during straight-line conditions, starting from an initial speed of 30 km/h.

3.5.6 Robustness analysis through Monte Carlo simulations



(a) Implemented Monte Carlo parameters distributions. (b) Distributions of σ_{peak} and v_{fin} resulting from the Monte Carlo analyses for the speed bump test.

Fig. 3.11 Robustness analysis through Montecarlo method.

To evaluate the robustness of the controllers to model uncertainties, external disturbances, and inaccuracies in estimating the road profile and tire-road friction, a Monte Carlo-based analysis was carried out. Specifically, 500 randomized simulations were executed for each controller configuration (SMC and NMPCs) across the speed bump test.

Uncertainty was introduced by modifying only the high-fidelity plant model, while maintaining nominal parameters in the prediction model. The perturbed parameters include: (i) an additional mass m_{add} relative to the nominal vehicle mass, (ii) a pure time delay t_{del} in the motor torque response, (iii) a scaling factor μ_{scal} and a time shift μ_{shift} applied to the tire-road friction coefficient, (iv) a scaling factor w_{scal} and time shift w_{shift} for the road profile, and (v) scaling factors w_{k_x} and w_{C_x} for the Pacejka tire model's longitudinal stiffness and shape factor. Notably, since SMC does not include wheel vertical dynamics, it remains unaffected by variations in w_{scal} and w_{shift} . The parameters distribution is reported in Figure 3.11a.

The resulting distributions of peak slip σ_{peak} and final velocity v_{fin} are presented in Figure 3.11b, while average values $\bar{\sigma}_{\text{peak}}$ and $\bar{v}_{\text{fin}}$, along with their standard deviations $\sigma_{\sigma_{\text{peak}}}^*$ and $\sigma_{v_{\text{fin}}}^*$, are reported in Table 3.3. The NMPC with full preview achieves superior robustness, with $\bar{\sigma}_{\text{peak}} = 0.055$ and $\sigma_{\sigma_{\text{peak}}}^* = 0.021$, and satisfies $\sigma_{\text{peak}} < 0.05$ in approximately 60% of the scenarios. Conversely, $\text{NMPC}^{\mu \text{ prev.}}$, $\text{NMPC}^{\text{w/o prev.}}$, and the integral SMC result in higher average σ_{peak} values of 0.118, 0.156, and 0.152, respectively, with standard deviations of 0.032, 0.023, and 0.025, demonstrating reduced robustness and traction performance.

The v_{fin} distributions show minimal variation across all configurations, with differences below 1%, indicating that the anticipatory actions of $\text{NMPC}^{\text{full prev.}}$ do not compromise longitudinal performance.

Lastly, the unfeasibility rate i_r , defined as the fraction of simulations where the optimal control problem could not be solved, remains consistently zero for all NMPC configurations. This confirms the reliability and numerical stability of the NMPC implementations under a broad set of operating conditions. Although a formal stability proof is not provided due to the complexity of the nonlinear system, the convergence of the cost function to zero during free response suggests alignment with Lyapunov stability theory [136].

Table 3.3 Monte Carlo analysis results, in terms of average values and standard deviations of σ_{peak} and v_{fin} , as well as unfeasibility rate i_r , across the considered 500 simulations.

	$\bar{\sigma}_{\text{peak}}$	$\bar{v}_{\text{fin}}$ [m/s]	$\sigma_{\sigma_{\text{peak}}}^*$	$\sigma_{v_{\text{fin}}}^*$ [m/s]	i_r
SMC	0.152	7.88	0.025	0.201	0
NMPC(w/o prev)	0.156	7.83	0.032	0.245	0
NMPC(μ prev)	0.118	7.83	0.023	0.255	0
NMPC(full prev)	0.055	7.77	0.021	0.268	0

3.6 Proof-of-concept experiments

3.6.1 testing set-up

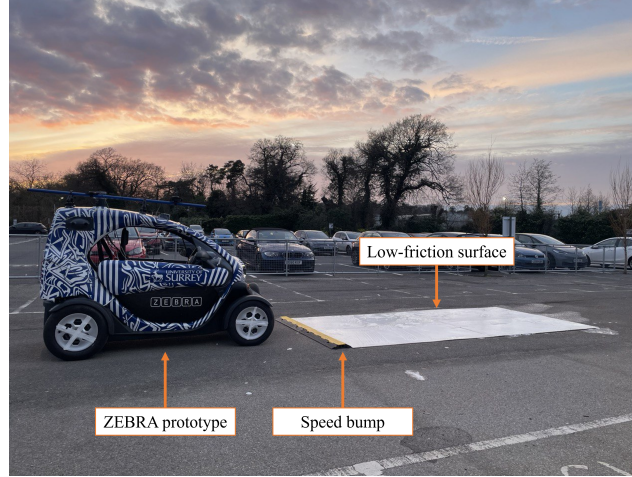


Fig. 3.12 The ZEBRA electric vehicle developed by the University of Surrey undergoing the test scenario consisting of a speed bump followed by a low- μ section, obtained by applying soap on acrylic boards.

Preliminary proof-of-concept experiments were conducted using the automated driving mode of the ZEBRA EV prototype introduced in Section 3.2.1. Figure 3.12 shows the test setup, which replicates the simulated speed bump scenario with an obstacle followed by a low-friction surface ($\mu \approx 0.2$), created using soap on acrylic boards.

To enable real-time execution of the NMPC algorithms on the dSPACE MicroAutoBox II, and to address the slow transient behavior of the ZEBRA powertrain (see Fig. 3.3), a variable time-step strategy was adopted during experiments, differing from the fixed-step configuration in simulations. The prediction horizon H_p was set to 240 ms, using four initial 10 ms steps followed by four 50 ms steps, while preserving a 10 ms control update rate. The integration step of the prediction model was increased from 1 ms to 5 ms.

Due to the notable pure time delay in the torque response (absent in simulation), preview signals used by $\text{NMPC}^{\text{full prev.}}$ and $\text{NMPC}^{\mu \text{ prev.}}$ were time-shifted to compensate for this delay. The same shift was also applied to the friction coefficient input for $\text{NMPC}^{\text{w/o prev.}}$, which otherwise would have yielded a slip ra-

tio response comparable to that of a passive EV. As a result, the experimental NMPC^{w/o prev} implementation effectively incorporates friction preview, though with constant μ over H_p and without road elevation information.

3.6.2 Experimental results

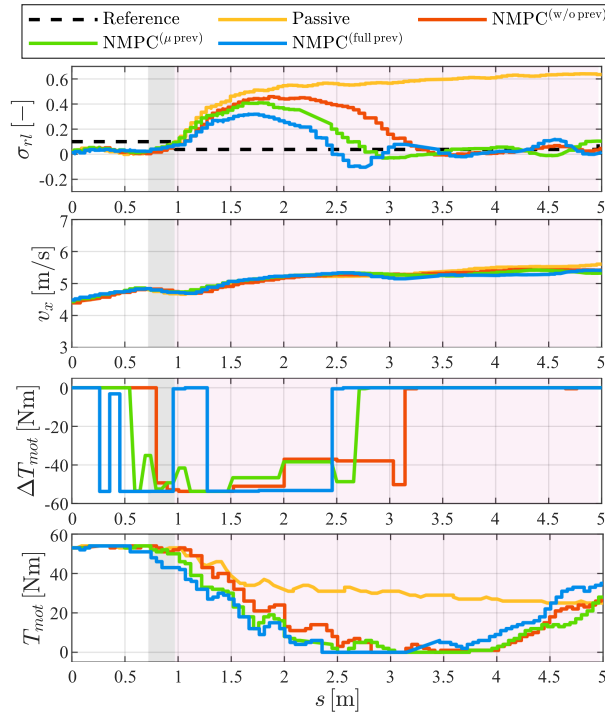


Fig. 3.13 Performance comparison of the considered NMPC controllers in terms of σ_{rl} , v_x , a_x , ΔT_{mot} , and T_{mot} profiles along the experimental speed bump test.

To ensure consistency, each controller configuration was tested through six repetitions of the same experimental maneuver. Figure 3.13 shows representative profiles of key variables as functions of s , while Figure 3.14 reports the average values of the longitudinal slip KPIs across repetitions, along with the corresponding ranges of σ_{peak} and $\hat{e}_\sigma$.

Due to the slow dynamics of the ZEBRA powertrain, all NMPC variants exhibit a bang-bang behavior with abrupt changes in the reference motor torque, clearly visible in the ΔT_{mot} profiles. As discussed, the actuation delay compensation allows

also $\text{NMPC}^{\text{w/o prev}}$ to act before the μ -jump. However, only $\text{NMPC}^{\text{full prev}}$ effectively anticipates the road disturbance (thanks to its consideration of vertical dynamics) reducing σ_{peak} to 0.31, while $\text{NMPC}^{\mu \text{ prev}}$ and $\text{NMPC}^{\text{w/o prev}}$ exceed 0.4.

All controllers exhibit similar behavior in terms of v_x . In the second half of the maneuver, the control effort diminishes (e.g., ΔT_{mot} at $s \approx 2.5$ m), as the controller anticipates the return to high-friction conditions.

Despite the lag in T_{mot} due to actuation delays, the KPIs confirm the superior performance of $\text{NMPC}^{\text{full prev}}$, which nearly halves $\hat{e}_\sigma$ compared to the baseline $\text{NMPC}^{\mu \text{ prev}}$. The experimental results are repeatable, as highlighted by the narrow error bars, e.g., with a maximum σ_{peak} variation of approximately 6% for $\text{NMPC}^{\text{full prev}}$ with respect to its average value.

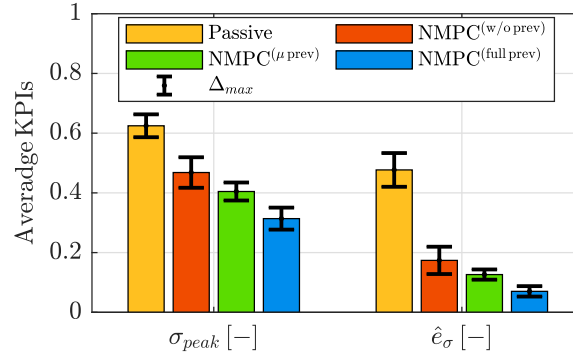


Fig. 3.14 Values of σ_{peak} and $\hat{e}_\sigma$ for the rear left wheel across the 24 experimental speed bump tests, covering all considered NMPC configurations. The histograms report the average values, while the error bars indicate the range of the respective KPI.

3.7 Concluding remarks

This chapter presented a novel nonlinear model predictive control (NMPC) formulation for traction control in electric vehicles equipped with centralized on-board powertrains, which explicitly accounts for the vertical dynamics induced by road irregularities through preview information.

Simulation results demonstrated that:

- For a nominal torque time constant $\tau = 25$ ms, a prediction horizon $H_p = 90$ ms combined with a controller sampling time $T_s = 10$ ms offers a favorable trade-off between traction performance and computational effort.
- In the presence of localized road events, the proposed NMPC^{full prev}, with preview on both road profile and tire-road friction, can nearly eliminate violations of the longitudinal tire slip constraint, while improving vehicle exit speed compared to the passive case.
- When accounting for slower powertrain dynamics (e.g., $\tau = 120$ ms), the benefits of NMPC^{full prev} are amplified, yielding over $2.5\times$ and $7\times$ reductions in the integral of tire slip violations compared to NMPC ^{μ prev} and NMPC^{w/o prev} / SMC, respectively.
- NMPC^{full prev} proved more robust to modeling uncertainties, external disturbances, and inaccurate estimations of friction and road elevation, as shown via Monte Carlo analysis under both regular and μ -split conditions.
- The controller also maintained high performance on ISO class B and C road profiles.

Preliminary experimental validations on speed bump tests confirmed the simulation results with good repeatability. Importantly, this work highlights the potential of leveraging electric powertrains as powerful enablers of advanced vehicle control functionalities. In particular, predictive and pre-emptive control strategies can enhance electric torque actuation even in scenarios with slower powertrain response dynamics.

The encouraging outcomes of NMPC^{full prev} suggest that such preview-based strategies may be instrumental in shaping next-generation traction control systems. Future work will focus on: (i) testing the controller in more complex driving scenarios with fully integrated estimators; (ii) extending the NMPC framework to jointly address ride comfort and vehicle stability through friction brake actuation; and (iii) conducting extensive experimental validation across a wide range of road and maneuvering conditions, including μ -split and cornering.

Chapter 4

Torque vectoring for battery electric vehicles

The ongoing transition toward electric mobility is enabling the development of innovative powertrain architectures that fully exploit the inherent controllability of electric traction systems. In this context, multi-motor electric vehicles provide the opportunity for individual wheel torque actuation, commonly referred to as torque vectoring [137]. This capability allows the powertrain to serve not only as a source of propulsion but also as a chassis actuator, enabling enhanced control of the lateral vehicle dynamics and contributing to improved active safety.

Among the various powertrain configurations, solutions based on in-wheel electric motors appear particularly promising due to their fast dynamic response and the absence of traditional driveline components such as differentials and half-shafts. These characteristics make in-wheel architectures especially suitable for advanced vehicle control strategies.

This chapter shifts the focus from the design and control of electric powertrains at the component level to the vehicle level, with an emphasis on multi-motor architectures. The objective is to investigate how vehicle dynamics and energy efficiency can be enhanced through torque vectoring control strategies that coordinate the torque distribution among the electric motors.

This chapter presents and discusses the development and experimental validation of advanced torque vectoring control strategies for electric vehicles with in-wheel motor architectures. The methodologies are directly derived from two works by

the author: Castellanos et al. [27], which focuses on handling limit prediction and agility enhancement, and Manca et al. [59], which introduces energy-aware torque allocation strategies.

The proposed torque vectoring control approach has been first validated in simulation using a rear-wheel-drive (RWD) in-wheel motor architecture developed within the European project Hiperform. Experimental validation has been carried out on a four-wheel-drive (4WD) in-wheel electric vehicle developed by SquadraCorse PoliTo, a Formula Student team, in real track conditions.

4.1 State of the art on torque vectoring control for electric vehicles

Different control strategies can be exploited for torque vectoring (TV) in fully electric vehicles. Typically, the steering angle information, which is a known exogenous disturbance applied by the driver, is used to generate either a yaw rate target or a direct yaw moment that modifies the dynamics of the vehicle chassis [138]. A comparison of feedback control techniques for torque vectoring is provided in [28]. Proportional Integral (PI) controllers are commonly used for yaw rate tracking [139], while adaptive linear quadratic regulators (LQR) have been applied to both rear-wheel drive [140] and all-wheel drive configurations [141, 142].

Sliding mode controllers (SMCs) are also widely adopted due to their robustness to disturbances and plant-model mismatches [143]. However, they are subject to chattering effects, which can be mitigated by advanced anti-chattering techniques [144, 145]. More sophisticated feedforward TV control variants have also been proposed, leveraging differential flatness [146] or input-output linearization techniques [147]. These approaches improve agility but suffer from stability due to their open-loop nature. To improve robustness, feedforward controllers are often coupled with state-feedback regulators.

Model Predictive Control (MPC) is increasingly being used in this context due to its ability to optimally manage system dynamics under state and input constraints. MPC-based TV controllers have been proposed to consider tire slip, actuator saturation, and handling envelope limits [58, 52, 148, 149]. A detailed comparison between linear and nonlinear MPC implementations is available in [149]. Nevertheless, the

real-time feasibility of these controllers remains a challenge, particularly when non-linear tire dynamics and inequality constraints are involved. These formulations often require softening strategies to avoid infeasibility and the use of tailored solvers.

More recently, attention has been given to energy-aware torque vectoring strategies. The overactuation typical of multi-motor electric vehicles allows for redundancy in generating the same yaw moment, opening the opportunity to minimize energy consumption while preserving vehicle dynamics. Some works propose the integration of energy models in predictive control frameworks, aiming to penalize high-efficiency losses in electric machines [150]. Others suggest heuristic or rule-based methods [151] for energy-optimized torque allocation. These strategies, sometimes grouped under the term “eco torque vectoring” (ECO-TV), remain an open research field, particularly regarding real-time applicability and trade-off tuning between energy saving and agility or safety.

4.2 Case study vehicles

The performance of the proposed controller are evaluated for the following case studies of battery electric vehicles equipped with in-wheel motors.

4.2.1 Case study A: RWD in-wheel SUV

The first case study features a full-electric B-SUV equipped with two in-wheel motors located in the rear axle. The main vehicle parameters are reported in Table 4.1.

Two in-wheel motors Elaphe M700 (version VD2) [152], are mounted on the rear axle of the vehicle. They are water-cooled outer rotor synchronous in-wheel motors with surface-mounted permanent magnets. Each motor is able to deliver a continuous torque of 400 Nm (maximum torque 700 Nm), 60 kW of maximum power. Both in-wheel motors are controlled in torque mode. The motors are directly connected to wheel hubs, in a direct drive arrangement. The efficiency map of the selected motor, are reported in Figure 4.1. The electric motors feature a response of 500 Nm/s, compliant with the required control functions.

Table 4.1 Vehicle data.

Vehicle parameter	Description	Value
m	Mass	1430 [kg]
J_z	Yaw moment of inertia	2059.2 [kg·m ²]
a	Distance of COG from front axle	0.996 [m]
b	Distance of COG from rear axle	1.494 [m]
h_{COG}	Distance of COG from ground	0.65 [m]
$t_{WF} = t_{WR}$	Track width	1.565 [m]
R_w	Wheel effective rolling radius	0.308 [m]
—	Tires	205/55r16

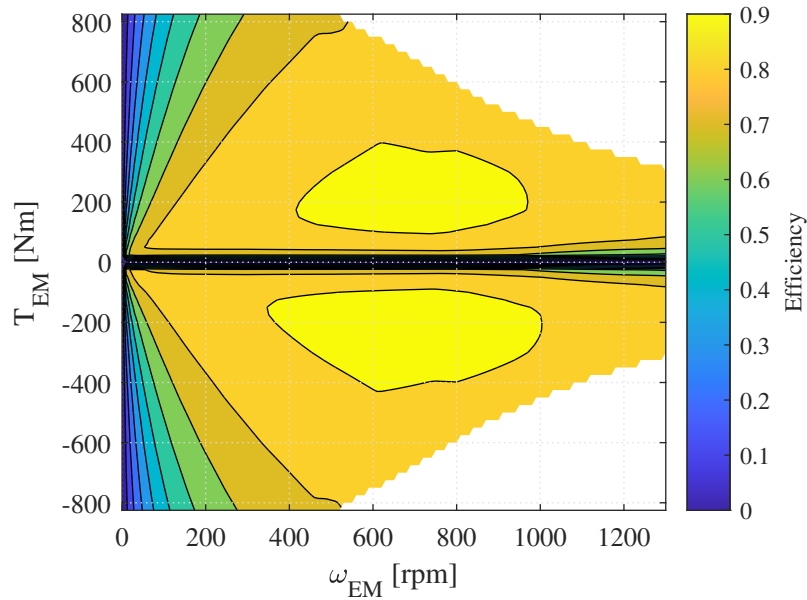


Fig. 4.1 Efficiency map of the Elaphe in-wheel motor.

4.2.2 Case study B: 4WD Formula Student vehicle

The second case study is the 2024 racecar prototype developed by Squadra Corse PoliTo. The vehicle features a carbon fiber monocoque chassis and is equipped with four in-wheel electric motors, each coupled to the wheels via a planetary gearbox. The main technical specifications of the vehicle are summarized in Table 4.2.

Table 4.2 SC24 vehicle data.

Description	Value
Mass without driver	207 [kg]
Front mass repartition	45 [%]
Wheelbase	1.525 [m]
Track	1.202 [m]
Center of gravity height from ground	0.28 [m]
Tires	185/40 R14 slick
Rims	R13 magnesium alloy
Aerodynamic lift coefficient	4.8
Aerodynamic drag coefficient	1.5
Front aerodynamic balance	58 [%]
Nominal HV battery pack capacity	7.7 [kWh]
Nominal HV battery pack voltage	564 [V]
0–100 km/h acceleration time	2.6 [s]
Maximum speed	122 [km/h]
Maximum lateral acceleration	2.5 [g]
Powertrain type	Electric 4WD
Maximum motor power (data sheet)	35 [kW]
Maximum regenerated power	40 [kW]
Transmission ratio	14.69



Fig. 4.2 Squadra Corse Polito 2024 prototype.

4.3 Control system

Figure 4.3 depicts the overall control scheme. The objective is to generate a corrective yaw moment by applying a differential torque through the in-wheel electric motors. The torque vectoring strategy produces two distinct yaw moment contributions: $M_{z,FF}$ and $M_{z,FB}$. The first is generated by a feedforward controller, which aims to enforce a desired vehicle response. The second is provided by an optimal state-feedback controller, which intervenes to stabilize the vehicle whenever its dynamics exceed the handling limits.

An extended Kalman filter (EKF) estimator, combined with a kinematic model, is used to estimate the vehicle's body sideslip angle. All components of the proposed control framework are discussed in detail in the following sections.

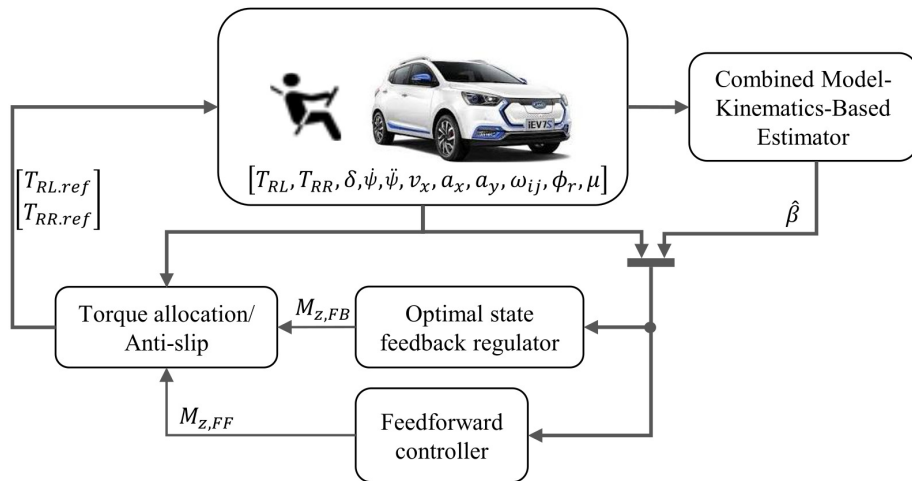


Fig. 4.3 Proposed Torque vectoring control scheme.

4.3.1 Vehicle model

The yaw moment and wheel forces are depicted in a top view of the vehicle in Figure 4.4.

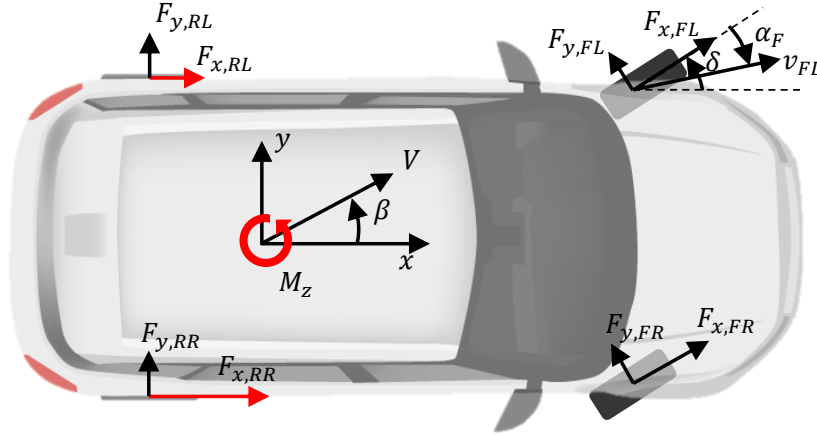


Fig. 4.4 Tire forces and yaw moment on the vehicle, for the RWD vehicle case study A.

The lateral dynamics of the vehicle is modelled in terms of yaw rate ($\dot{\psi}$) and sideslip angle (β) using a dual-track vehicle model, and based on the assumptions of negligible force due to road bank angle, known and constant vehicle speed, small sideslip angle and steering angle δ , negligible aerodynamic forces, and negligible tire self-alignment moment:

$$mv_x(\dot{\beta} + \dot{\psi}) = F_{yF} + F_{yR} \quad (4.1)$$

$$J_z \ddot{\psi} = aF_{yF} - bF_{yR} + M_z \quad (4.2)$$

where m is the vehicle mass, v_x is the vehicle longitudinal velocity, J_z is the yaw moment of inertia, a and b are the longitudinal distances from the centre of gravity. M_z is a yaw moment actively generated by the rear in-wheel motor when a differential torque is applied.

The front and rear tire lateral forces (F_{yF}, F_{yR}) are given by:

$$\begin{aligned} F_{y,F} &= F_{y,FL}(\alpha_F, F_{z,FL}) + F_{y,FR}(\alpha_F, F_{z,FR}) \\ F_{y,R} &= F_{y,RL}(\alpha_R, F_{z,RL}) + F_{y,RR}(\alpha_R, F_{z,RR}) \end{aligned} \quad (4.3)$$

with front and rear slip angles given by:

$$\begin{aligned}\alpha_F &= \beta + \frac{a\dot{\psi}}{v_x} - \delta \\ \alpha_R &= \beta - \frac{b\dot{\psi}}{v_x}\end{aligned}\tag{4.4}$$

The vertical forces $F_{z,ij}$ are calculated using the weight distribution while accounting for longitudinal and lateral acceleration of the vehicle (a_x, a_y), as measured on-board:

$$\begin{aligned}F_{z,FL} &= m \cdot \left(\frac{b}{l} - \frac{h_{COG}}{l} a_x \right) \left[\frac{1}{2} - \frac{h_{COG} \cdot a_y}{b_F \cdot g} \right] \\ F_{z,FR} &= m \cdot \left(\frac{b}{l} - \frac{h_{COG}}{l} a_x \right) \left[\frac{1}{2} + \frac{h_{COG} \cdot a_y}{b_F \cdot g} \right] \\ F_{z,RL} &= m \cdot \left(\frac{a}{l} + \frac{h_{COG}}{l} a_x \right) \left[\frac{1}{2} - \frac{h_{COG} \cdot a_y}{b_R \cdot g} \right] \\ F_{z,RR} &= m \cdot \left(\frac{a}{l} + \frac{h_{COG}}{l} a_x \right) \left[\frac{1}{2} + \frac{h_{COG} \cdot a_y}{b_R \cdot g} \right]\end{aligned}\tag{4.5}$$

where l is the vehicle wheelbase, and b_F and b_R are the front and rear track widths, respectively.

Equations (4.1)–(4.5) represent the nominal model of the vehicle and can be condensed into the nonlinear time-domain representation:

$$\dot{\xi} = f(\xi, u, \delta, p),\tag{4.6}$$

with the state vector $\xi = [\beta, \dot{\psi}]^\top$, the yaw moment $M_z \equiv u$ as the manipulated input, the steering angle (δ) as a known disturbance input, and the vector $p = [v_x, a_x, a_y]^\top$ grouping the time-varying parameters: longitudinal speed, longitudinal acceleration, and lateral acceleration of the chassis, respectively. All these signals are assumed to be measured quantities available from the vehicle control unit (VCU).

Hereinafter, the nonlinear system (4.6) is adopted as the nominal vehicle model. The analysis carried out in this work refers to a vehicle having the data reported in Tables 4.1 and 4.2, for the respective case studies.

4.3.2 Tire model

The lateral tire forces in Equation (4.3) are computed considering the time-varying distribution of vertical load. For the B-SUV vehicle (Case Study A), a simplified nonlinear model is adopted, fitted offline to a Pacejka-based dataset referring to the tire under study (205/55R16). The model is:

$$F_{y,ij} = k_{\text{red},ij} \left(k_1 - \frac{F_{z,ij}}{k_2} \right) \cdot F_{z,ij} \cdot \arctan(k_3 \cdot \alpha_{ij}), \quad (4.7)$$

with $i = F, R$ and $j = L, R$, where $k_{\text{red},ij}$ is a reduction factor that accounts for the friction limitations under combined lateral and longitudinal slip. The parameters are identified offline via nonlinear least-squares fitting using MATLAB, yielding: $k_1 = 0.6819, k_2 = 1.385 \times 10^5, k_3 = 40.85$.

The fitting procedure achieves a normalized root mean square error (NRMSE) of 85.6%, which is considered sufficient for vehicle-level simulation purposes. Figure 4.5 shows the comparison between the fitted curve and the original Pacejka dataset.

For the 4WD racecar prototype (Case Study B), a full Pacejka tire model is instead implemented in the internal vehicle simulation. The parameters are imported directly from the official `.tir` file provided by the tire manufacturer. Due to confidentiality agreements, the coefficients are not disclosed in this work.

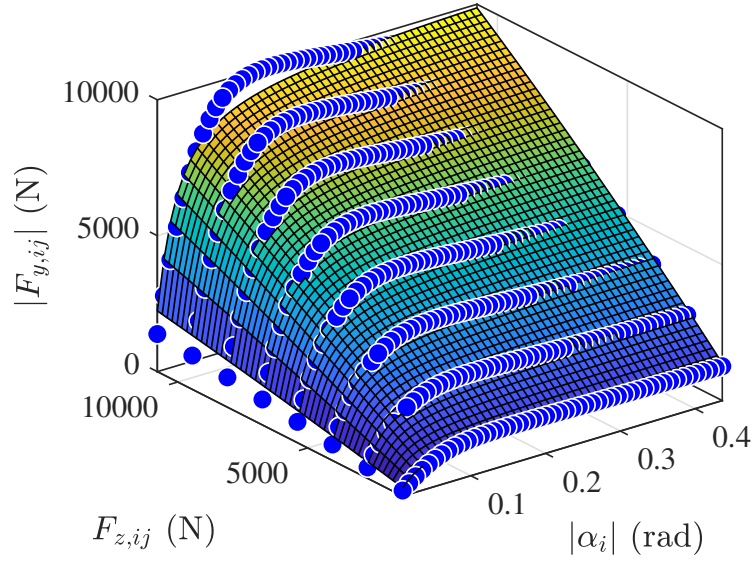


Fig. 4.5 Comparison of Equation (4.7) (surface) to the data of the tire 205/55r16 (blue dotted lines). The latter is obtained from the Pacejka magic formula.

4.3.3 Feedforward controller

The feedforward (FF) controller is designed to generate a yaw moment $M_{z,FF}$ that forces the vehicle to emulate the yaw dynamics response of a desired reference vehicle.

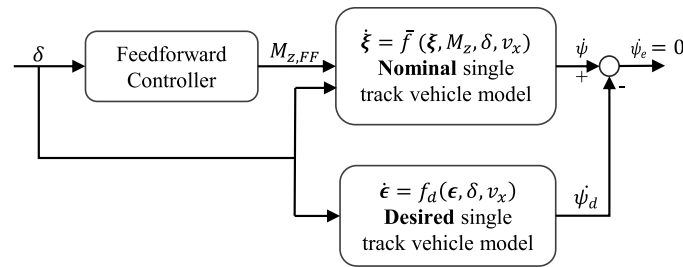


Fig. 4.6 Feedforward control scheme.

The approach relies on comparing the nominal dynamics of the actual vehicle and the desired model. Both are described using the single-track linear model:

$$\dot{\xi} \approx \tilde{A}(v_x)\xi + \tilde{B}M_{z,FF} + \tilde{B}_d\delta, \quad (4.8)$$

where $\xi = [\beta, \dot{\psi}]^\top$ is the state vector, δ is the steering angle, and the matrices $\tilde{A}(v_x), \tilde{B}, \tilde{B}_d$ are defined as:

$$\tilde{A} = \begin{pmatrix} \frac{-C_{\alpha,F} - C_{\alpha,R}}{mv_x} & \frac{-C_{\alpha,F}a + C_{\alpha,R}b}{mv_x} \\ \frac{-C_{\alpha,F}a - C_{\alpha,R}b}{J_z} & \frac{-C_{\alpha,F}a^2 + C_{\alpha,R}b^2}{J_z v_x} \end{pmatrix}, \quad \tilde{B} = \begin{pmatrix} 0 \\ \frac{1}{J_z} \end{pmatrix}, \quad \tilde{B}_d = \begin{pmatrix} \frac{C_{\alpha,F}}{mv_x} \\ \frac{C_{\alpha,F}a}{J_z} \end{pmatrix}. \quad (4.9)$$

Similarly, the desired model is given by:

$$\dot{\varepsilon} = \bar{A}(v_x)\varepsilon + \bar{B}(v_x)\delta, \quad (4.10)$$

with $\varepsilon = [\bar{\beta}, \bar{\dot{\psi}}]^\top$, and $\bar{A}(v_x), \bar{B}(v_x)$ having the same structure but possibly different parameters (e.g., a reduced yaw inertia $\bar{J}_z = 0.75J_z$ to simulate a more agile car).

To design the FF controller, the yaw rate error $\dot{\psi}_e = \bar{\dot{\psi}} - \dot{\psi}$ is enforced to be zero. The feedforward reacts in open loop directly as a consequence of the applied steering angle. Using Laplace transforms, the FF controller transfer function becomes:

$$FF(s) = \frac{M_{z,FF}(s)}{\delta(s)} = \frac{G_{des}(s) - G_{pd}(s)}{G_{pu}(s)} = C_{FF}(sI - A_{FF})^{-1}B_{FF} + D_{FF}, \quad (4.11)$$

where $G_{des}(s) = \frac{r_d(s)}{\delta(s)}$, $G_{pd}(s) = \frac{r(s)}{\delta(s)}$, and $G_{pu}(s) = \frac{r(s)}{M_{z,FF}(s)}$.

To enable implementation, this transfer function is cast into a linear time-varying state-space form:

$$\begin{aligned} \dot{\zeta}(t) &= A_{FF}(t)\zeta(t) + B_{FF}(t)\delta(t) \\ M_{z,FF}(t) &= C_{FF}(t)\zeta(t) + D_{FF}(t)\delta(t), \end{aligned} \quad (4.12)$$

where the matrices $A_{FF}, B_{FF}, C_{FF}, D_{FF}$ are symbolically computed in MATLAB at each time step based on current vehicle parameters. The system is then discretized to obtain the real-time control law $M_{z,FF,k}$.

Only the yaw inertia was modified in the desired model for the case study presented in this work, while all other vehicle parameters remained equal to the nominal configuration. The investigation of the influence of other parameter modifications in the desired model can be a future development of the proposed control solution. In Figure 4.7 the Bode response of the FF control is reported.

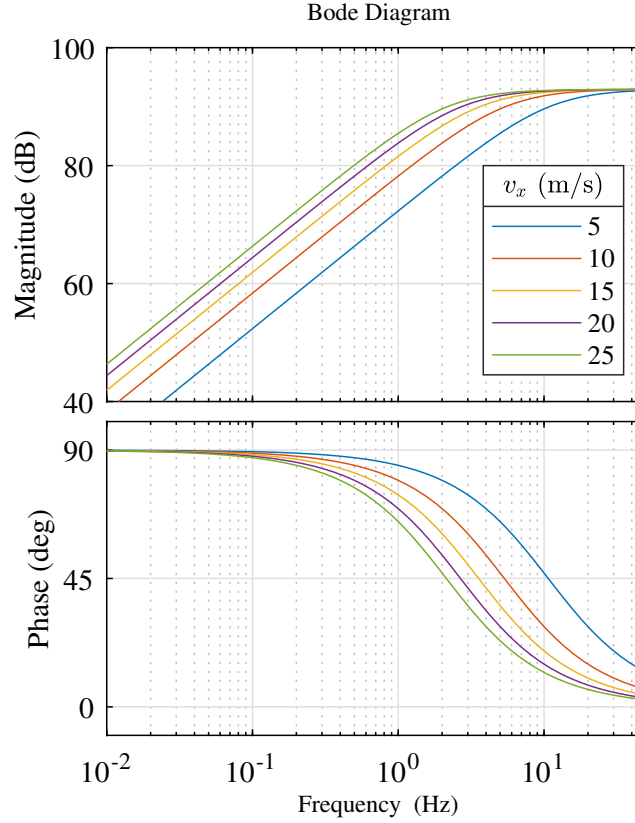


Fig. 4.7 Feedforward control scheme.

4.3.4 State-feedback control

A state-feedback controller is introduced to monitor the vehicle's motion with respect to its dynamic handling limits. When the vehicle tends to exceed the limits in terms of yaw rate or sideslip angle, a corrective yaw moment $M_{z,FB}$ is applied. The controller is formulated as a finite-horizon optimal control problem:

$$\min_{\Delta u_0, \dots, \Delta u_{N-1}} \frac{1}{2} \sum_{i=0}^{N-1} (\|e_{i|k}\|_Q^2 + \|u_{i|k}\|_{R_u}^2 + \|\Delta u_{i|k}\|_{R_{\Delta u}}^2) \quad (4.13)$$

subject to:

$$\xi_{i+1|k} = A_k \xi_{i|k} + B_k u_{i|k} + B_{d,k} \delta_k, \quad i = 0, \dots, N-1 \quad (4.14)$$

$$u_{i|k} = u_{i-1|k} + \Delta u_{i|k}, \quad i \geq 0 \quad (4.15)$$

$$u_{-1|k} = M_{z,\text{sat}|k-1} \quad (4.16)$$

$$\xi_{0|k} = \hat{\xi}_k \quad (4.17)$$

$$e_{i|k} = \xi_{i|k} - \xi_{\text{ref},i|k}, \quad i = 0, \dots, N-1 \quad (4.18)$$

with $\xi_{i|k} = [\beta_{i|k}, \psi_{i|k}]^\top$ and control input $u_{i|k} = M_{z,i|k}$. Only the first optimal increment Δu_0^* is applied at each time step:

$$M_{z,\text{FB}} = u_{k-1} + \Delta u_0^*. \quad (4.19)$$

Reference generation strategies

The reference trajectory $\xi_{\text{ref},i|k} = [\beta_{\text{ref},i|k}, \psi_{\text{ref},i|k}]^\top$ is computed through a smooth saturation function that ensures compatibility with the handling limits. The same formulation is adopted for the sideslip angle in both case studies:

$$\beta_{\text{ref},i|k} = \beta_{\text{max}} \cdot \tanh\left(\frac{\beta_{i|k}}{\beta_{\text{max}}}\right), \quad (4.20)$$

where β_{max} is set to:

$$\beta_{\text{max}} = 0.02 \mu g. \quad (4.21)$$

This formulation prevents the controller from overreacting to potentially noisy or large sideslip estimates, ensuring smooth and bounded corrections.

The yaw rate reference instead differs depending on the control objective:

- **Case Study A (Stability-oriented):** to saturate within the safety limits:

$$\psi_{\text{ref},i|k} = \psi_{\text{max}} \cdot \tanh\left(\frac{\psi_{i|k}}{\psi_{\text{max}}}\right), \quad (4.22)$$

with $\dot{\psi}_{\max} = 0.85 \mu g / V_{\text{COG}}$.

- **Case Study B (Performance-oriented):** the reference is based on a desired steady-state yaw rate response:

$$\dot{\psi}_{\text{ss},i|k} = \frac{v_{x,k} \delta_k}{K_r (1 + K_{\text{us}} v_{x,k}^2)}, \quad (4.23)$$

followed by saturation:

$$\dot{\psi}_{\text{ref},i|k} = \dot{\psi}_{\max} \cdot \tanh \left(\frac{\dot{\psi}_{\text{ss},i|k}}{\dot{\psi}_{\max}} \right). \quad (4.24)$$

Where K_{us} is the vehicle understeering coefficient, and K_r a tuning factor. This formulation allows a unified structure of the optimal control problem while adapting the behavior according to the application objective: limit violation avoidance in Case A, and linear yaw response enhancement in Case B. In this study, the steering angle and the longitudinal speed is considered constant in the prediction horizon, but preview-based techniques can be implemented.

Predictive implementation

To avoid embedding nonlinear expressions directly in the cost function (4.13), the state targets prediction $\xi_{\text{ref},i|k}$ is computed externally. A state predictor simulates the system evolution based on the latest optimal input sequence:

$$\left[\hat{\xi}_{0|k}, \dots, \hat{\xi}_{N|k} \right]^\top = \mathcal{X} \left(\hat{\xi}_{0|k}, \Delta u_{i=1:N-1|k-1}^*, \delta_k \right), \quad (4.25)$$

and the predicted target vector is assembled as:

$$\mathcal{X}_{\text{ref}} = \left[\xi_{\text{ref},0|k}^\top, \dots, \xi_{\text{ref},N|k}^\top \right]^\top. \quad (4.26)$$

This decoupling maintains convexity of the optimization problem and reduces computational burden while preserving accuracy in the prediction of handling limit violations and references.

Solving the quadratic programming (QP) problem

Once the cost function (4.13) and constraints (4.14)–(4.18) are defined, the optimal control problem is formulated as a standard QP with equality constraints. The weighting matrices are normalised using bounds on the predicted variables:

$$Q = \begin{bmatrix} \frac{1}{\beta_{\max}^2} & 0 \\ 0 & \frac{1}{\dot{\psi}_{\max}^2} \end{bmatrix}, \quad R_u = \frac{1}{M_{z,\max}^2}, \quad R_{\Delta u} = \frac{1}{\Delta M_{z,\max}^2} \quad (4.27)$$

The bounds on the applied yaw moment and its variation are defined as:

$$M_{z,\max} = (|T_{RR,\max}| + |T_{RL,\max}|) \cdot \frac{b_R}{2R_w} \quad (4.28)$$

$$\Delta M_{z,\max} = (|\Delta T_{RR,\max}| + |\Delta T_{RL,\max}|) \cdot \frac{b_R}{2R_w} \quad (4.29)$$

To solve the QP, the optimal control law is reformulated by expressing (4.14)–(4.18) over the horizon in batch form. This leads to a compact quadratic cost:

$$\mathcal{V}^* = \min_{\Delta u} \frac{1}{2} \Delta u^\top \mathcal{M} \Delta u + g^\top \Delta u + \tilde{V}, \quad (4.30)$$

where $\mathcal{M}$ is the Hessian matrix (positive definite), g is the linear term depending on the predicted state $\hat{\xi}_k$, previous input u_{k-1} , steering command δ_k , and reference $\mathcal{X}_{\text{ref}}$. The term $\tilde{V}$ is constant and does not affect the solution.

Solving (4.30) yields the optimal input variation:

$$\Delta u^* = -\mathcal{M}^{-1} g = \Delta u^* \left(\hat{\xi}_k, u_{k-1}, \delta_k, \mathcal{X}_{\text{ref}} \right) \quad (4.31)$$

and thus the first element Δu_0^* is applied as in (4.19).

This formulation ensures a computationally efficient and convex optimisation. Notably, the state feedback controller acts differently than a pure feedback control strategy since it uses the measured steering disturbance and an approximation of the state target evolution to calculate the optimal yaw moment variation that minimizes the violation of the limits of handling. The total applied yaw moment at each instant

is the sum of the feedforward contribution $M_{z,FF}$ and the optimal feedback correction $M_{z,FB}$.

4.3.5 Combined model-kinematics-based estimation of sideslip angle

Accurate estimation of the vehicle sideslip angle β is crucial for enhancing stability-oriented control. In this work, a hybrid estimation strategy is adopted, combining a model-based Extended Kalman Filter (EKF) with a kinematics-based formulation for $\dot{\beta}$.

The nonlinear vehicle dynamics is rewritten in hybrid form:

$$\dot{\xi} = f(\xi, u, \delta, \beta, \mathbf{w}_n, t), \quad (4.32)$$

$$\mathbf{z}_k = g(\xi_k, u_k, \delta_k, p_k, \mathbf{v}_{nk}), \quad (4.33)$$

where $\mathbf{w}_n(t) \sim \mathcal{N}(0, \tilde{Q})$ is continuous-time process noise and $\mathbf{v}_{nk} \sim \mathcal{N}(0, \tilde{R})$ is discrete-time measurement noise. The output vector is defined as:

$$\mathbf{z} = \begin{bmatrix} \psi & F_{yF} & F_{yR} \end{bmatrix}^\top \quad (4.34)$$

The lateral forces F_{yF}, F_{yR} are computed from vehicle measurements ($\dot{\psi}_{\text{meas}}, a_y$) and parameters (m, J_z, l_F, l_R) as:

$$\hat{F}_{yF} = \frac{ma_y l_R + J_z \ddot{\psi}_{\text{meas}}}{a + b}, \quad (4.35)$$

$$\hat{F}_{yR} = \frac{ma_y l_F - J_z \ddot{\psi}_{\text{meas}}}{a + b} \quad (4.36)$$

The EKF algorithm proceeds in three main steps:

(1) Initialisation Set initial state estimates and covariance:

$$\hat{\xi}_0^+ = \mathbb{E}(\xi_0), \quad (4.37)$$

$$P_0^+ = \mathbb{E} \left[(\xi_0 - \hat{\xi}_0^+) (\xi_0 - \hat{\xi}_0^+)^{\top} \right] \quad (4.38)$$

(2) Time update (prediction) Propagate state and covariance from $k-1$ to k^- :

$$\dot{\xi} = f(\hat{\xi}, u, \delta, p, 0), \quad (4.39)$$

$$\dot{P} = -PH^{\top}R^{-1}HP + FP + PF^{\top} + \tilde{Q} \quad (4.40)$$

Integration starts with $\hat{\xi}_{k-1}^+$ and P_{k-1}^+ . At the end of prediction:

$$\hat{\xi}_k^- = \hat{\xi}, \quad P_k^- = P$$

The predicted output is:

$$\hat{\mathbf{z}}_k = g \left(\hat{\xi}_k^-, u_k, \delta_k, p_k, 0 \right) \quad (4.41)$$

(3) Measurement update (correction)

$$K_k = P_k^- H^{\top} \left(H P_k^- H^{\top} + \tilde{R} \right)^{-1} \quad (4.42)$$

$$\hat{\xi}_k^+ = \hat{\xi}_k^- + K_k (\mathbf{z}_k - \hat{\mathbf{z}}_k) \quad (4.43)$$

$$P_k^+ = (I - K_k H) P_k^- \quad (4.44)$$

After this step, the updated state estimate is $\hat{\xi}_k^+ = [\hat{\beta}_{\text{EKF}}, \dot{\hat{\beta}}_{\text{EKF}}]^{\top}$.

Kinematic augmentation of $\dot{\beta}$

To avoid direct integration of $\dot{\beta}_{\text{kin}}$, which is sensitive to noise and bias, a filtered combination of $\hat{\beta}_{\text{EKF}}$ and $\dot{\beta}_{\text{kin}}$ is used as proposed in [153]:

$$\hat{\beta} = \frac{1}{\tau_s + 1} \hat{\beta}_{\text{EKF}} + \frac{\tau}{\tau_s + 1} \dot{\beta}_{\text{kin}} \quad (4.45)$$

with $\tau = \frac{10}{2\pi}$. The first term filters the EKF output to suppress high-frequency noise, while the second term effectively integrates $\dot{\beta}_{\text{kin}}$ at higher frequencies. This formulation eliminates the need for explicit numerical integration and improves estimation robustness, especially during transient conditions.

4.3.6 Torque allocation

The generation of the desired yaw moment M_z is achieved by introducing a differential torque between the in-wheel motors on the same axle. In the case of the RWD architecture adopted in Case Study A, the longitudinal torque requested by the driver is equally split between the rear motors as a baseline value:

$$T_{\text{bias}} = \frac{T_{\text{req}}}{2} \quad (4.46)$$

To superimpose a yaw moment, an additional differential torque ΔT is introduced such that:

$$T_{RR,\text{ref}} = T_{\text{bias}} + \Delta T \quad (4.47)$$

$$T_{RL,\text{ref}} = T_{\text{bias}} - \Delta T \quad (4.48)$$

The torque imbalance ΔT is directly computed from the total yaw moment command M_z as:

$$\Delta T = \frac{M_z R_w}{2t w_R} \quad (4.49)$$

where R_w is the wheel rolling radius and b_R is the rear track width. The total yaw moment M_z results from the combination of the feedforward and feedback components:

$$M_z = M_{z,\text{FF}} + M_{z,\text{FB}} \quad (4.50)$$

This formulation is implemented at each control step, with the updated yaw moment command from the previous interval used to initialise the feedback controller. The reference torques are then saturated according to the traction control functions.

In the Case Study B (4WD high-performance vehicle), the same approach is extended to all four wheels. The longitudinal torque is statically distributed between front and rear axles according to the vehicle's mass repartition. The yaw moment is generated by adjusting the relative torque across the left and right motors of each axle, while ensuring the overall traction effort is preserved.

4.3.7 Energy-efficient torque allocation

An alternative energy-efficient torque allocation formulation is presented. The function is assessed in simulation, applied to a variant of the Case-A, the B-SUV with 4 in-wheel electric motors with the characteristics reported in Figure 4.1. The proposed torque allocation layer computes an optimal distribution of motor torques that simultaneously satisfies the overall traction request T_{req} and the desired yaw moment M_z , while minimizing energy losses and ensuring feasibility under motor constraints. The problem is formulated as a quadratic programming (QP) optimization:

$$\min_x \left(\frac{1}{2} x^\top H x + f^\top x \right) \quad (4.51)$$

subject to:

$$\begin{cases} A_{\text{eq}} x = b_{\text{eq}} \\ Ax \leq b \\ lb \leq x \leq ub \end{cases} \quad (4.52)$$

The decision vector is defined as:

$$x = [T_{FL}, T_{FR}, T_{RL}, T_{RR}, S_{T_{\text{req}}}, S_{M_z}]^\top$$

where $S_{T_{\text{req}}}$ and S_{M_z} are slack variables associated with the total traction and yaw moment constraints. These slack variables are penalized in the cost function to prioritize accurate tracking of the requests.

The equality constraints encode the torque balance and moment generation:

$$\begin{cases} T_{FL} + T_{FR} + T_{RL} + T_{RR} + S_{T_{\text{req}}} = T_{\text{req}} \\ \frac{R_w}{2} \left(\frac{T_{FR} - T_{FL}}{t_{wF}} + \frac{T_{RR} - T_{RL}}{t_{wR}} \right) + S_{M_z} = M_z \end{cases} \quad (4.53)$$

The corresponding equality matrices are:

$$A_{\text{eq}} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 0 \\ -\frac{R_w}{2t_{wF}} & \frac{R_w}{2t_{wF}} & -\frac{R_w}{2t_{wR}} & \frac{R_w}{2t_{wR}} & 0 & 1 \end{bmatrix}, \quad b_{\text{eq}} = \begin{bmatrix} T_{\text{req}} \\ M_z \end{bmatrix}$$

The inequality constraints guarantee consistency between total applied torque and moment sign:

$$Ax \leq b \quad (4.54)$$

with:

$$A = \begin{bmatrix} -\frac{t_{wf}}{R_w} & \frac{t_{wf}}{R_w} & -\frac{t_{wr}}{R_w} & \frac{t_{wr}}{R_w} & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 \end{bmatrix} \quad b = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Bounds on each motor torque are defined to respect minimum and maximum torque limits of the electric motor:

$$\begin{aligned} lb &= -k_{\text{reg}} T_{\text{max,EM},i} \\ ub &= T_{\text{max,EM},i} \end{aligned} \quad (4.55)$$

The objective function is designed to minimize power losses:

$$J = P_{\text{loss,EM}} + P_{\text{loss,long}} \quad (4.56)$$

Here, $P_{\text{loss,EM}}$ are the electrical losses from the e-motors (e.g., copper and iron losses), while $P_{\text{loss,long}}$ accounts for longitudinal slip losses.

The electric power losses $P_{\text{loss,EM}}$ are computed based on the motor operating point, using the speed–torque–efficiency maps of the electric machines. The instantaneous power loss is defined differently for traction and braking operation. In traction mode, it is computed as the difference between the input electrical power and the output mechanical power, while in braking mode, the expression is reversed to account for regenerative operation:

$$P_{\text{loss,EM}} = \begin{cases} \frac{T \omega_{\text{EM}}}{\eta_{\text{EM}}} - T \omega_{\text{EM}}, & \text{traction} \\ T \omega_{\text{EM}} - \eta_{\text{EM}} T \omega_{\text{EM}}, & \text{braking} \end{cases} \quad (4.57)$$

where T is the torque applied by the electric motor, ω_{EM} is the rotor speed, and η_{EM} is the efficiency at the corresponding operating point. To enable a real-time and computationally efficient estimation of $P_{\text{loss,EM}}$ without directly accessing the efficiency maps, a second-order polynomial approximation of the electric power P_{el} is adopted:

$$P_{\text{el,est}} = a_1 \omega_{\text{EM}} T + a_2 \omega_{\text{EM}}^2 T + a_3 \omega_{\text{EM}} T^2 + a_4 \omega_{\text{EM}} + a_5 T \quad (4.58)$$

The coefficients of this model are identified through a least-squares fit of the motor efficiency curves, achieving a fitting accuracy of 96.51%. Thanks to this approximation, the motor losses can be efficiently computed at each control step using only the measured torque and speed, and are directly included in the quadratic cost function of the torque allocator.

The longitudinal slip power losses are related to the tire forces and the relative velocity between the tire contact patch and the wheel. These losses are computed as:

$$P_{\text{loss,long}} = F_x (v_{x,w} - \omega_w R_e) \approx \frac{T}{R_e} (v_{x,w} - \omega_w R_e) \quad (4.59)$$

where F_x is the longitudinal tire force, T is the applied motor torque, ω_w is the wheel angular velocity, and R_e is the effective rolling radius. The term $v_{x,w}$ represents the longitudinal component of the wheel center velocity in the wheel frame and can be computed for each wheel ij as:

$$v_{x,ij} = v_x \cos(\delta_i - \beta) \pm \left(\psi \cdot \sqrt{\left(\frac{a}{R} + \frac{tw_F}{2R}\right)^2 + \left(\frac{tw_F}{2a}\right)^2} \cdot \sin\left(\tan^{-1}\left(\frac{tw_F}{2a}\right)\right) \right) \quad (4.60)$$

The quadratic cost (4.51) is defined by the positive definite Hessian H , built as a diagonal matrix including the torque penalty terms and slack penalties. The vector f contains the linear cost terms, including the dissipation maps and load transfer components.

Thanks to convexity, the QP problem admits a unique solution and is solved using an active-set algorithm in real-time.

4.4 Simulation Results – Case Study A: RWD Vehicle

The performance of the proposed torque vectoring controller, including a nonlinear optimal feedback and a feedforward component, is assessed through co-simulation between Matlab/Simulink and CarSim. Both controllers operate at 50 Hz, while the inner anti-slip loop runs at 100 Hz. The prediction horizon is set to $N = 30$, with maximum sideslip and yaw rate deviations limited to $\beta_{\max}$ and $\psi_{\max}$, respectively. Input weights R_u and $R_{\Delta u}$ follow the normalization criteria discussed in Equations 4.21 – 4.22. Motor torque limits $T_{RL,\max}$, $T_{RR,\max}$ are updated at each step from map-based boundaries, while $\Delta M_{z,\max} = 1000$ Nm.

The controller is tested in both open-loop and closed-loop conditions, with results compared against a passive baseline vehicle featuring no yaw moment control and equal rear torque distribution.

4.4.1 Open-Loop Manoeuvres

The slow ramp steer (SRS) test, conducted at 100 km/h under low adhesion ($\mu = 0.5$), evaluates the steady-state lateral dynamics, at the limits of vehicle controllability. The steering wheel angle δ_{sw} increases from 0° to 100° at $1^\circ/\text{s}$. As shown in Figure 4.8, both vehicles behave similarly for lateral acceleration below 0.3 g. However, at higher values, the controlled vehicle exhibits a smoother transition from linear to

nonlinear regions. The peak sideslip angle is reduced by 36%, improving rear stability, mainly due to the state feedback regulator.

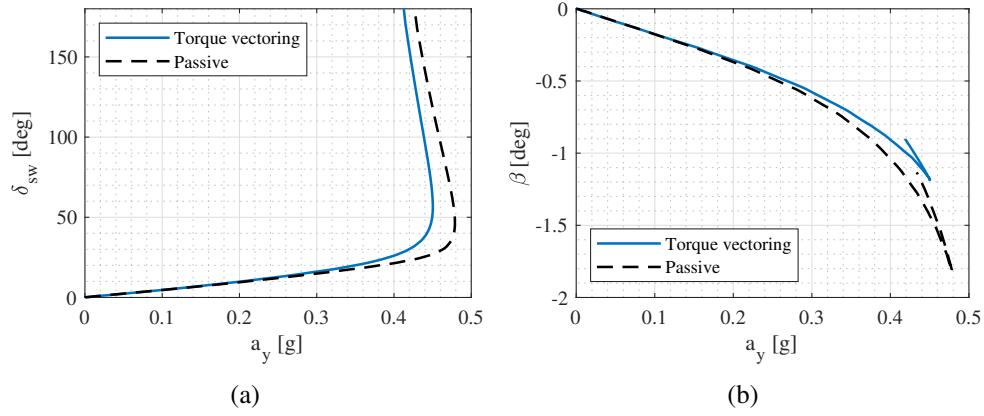


Fig. 4.8 SRS manoeuvre at 100 km/h, $\mu = 0.5$. Controlled vehicle: blue solid line. Passive vehicle: black dotted line. (a) δ_{sw} vs. a_y ; (b) β vs. a_y .

Transient steering dynamics are assessed through the sine sweep (SSI) test at 100 km/h on dry asphalt ($\mu = 1$). Figure 4.9 reports the frequency response between δ_{sw} and r . The controller shifts the natural yaw resonance frequency 30% higher and increases the magnitude of the resonance peak, improving agility. Additionally, the phase lag is reduced below 1.1 Hz, indicating faster response. These enhancements are primarily attributed to the feedforward contribution.

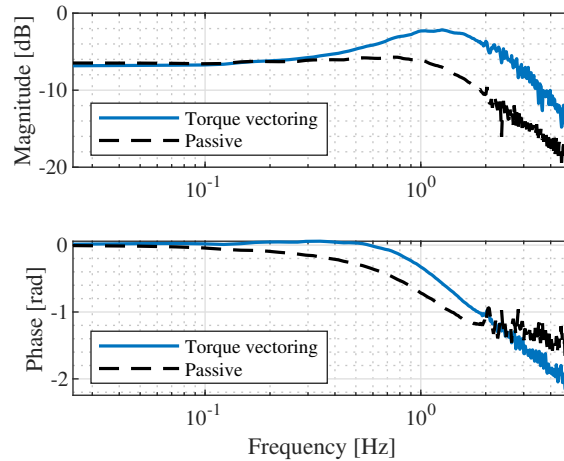


Fig. 4.9 SSI manoeuvre at 100 km/h, $\mu = 1$. Frequency response function between δ_{sw} and r . Controlled: blue; passive: black.

4.4.2 Closed-Loop Manoeuvres

Controller effectiveness is further evaluated through a double lane change (DLC) manoeuvre at 50 km/h on dry asphalt. As illustrated in Figure 4.10, the Lissajous diagram shows that the controlled vehicle exhibits reduced yaw rate hysteresis and better linearity between steering input and yaw response. The corrective yaw moment provided by the state feedback regulator increases as the vehicle approaches its stability limits, and the sideslip angle is consistently reduced by up to 29%. The simulated trajectory adheres more closely to the reference, with a goodness-of-fit of 64% versus 61% for the passive case.

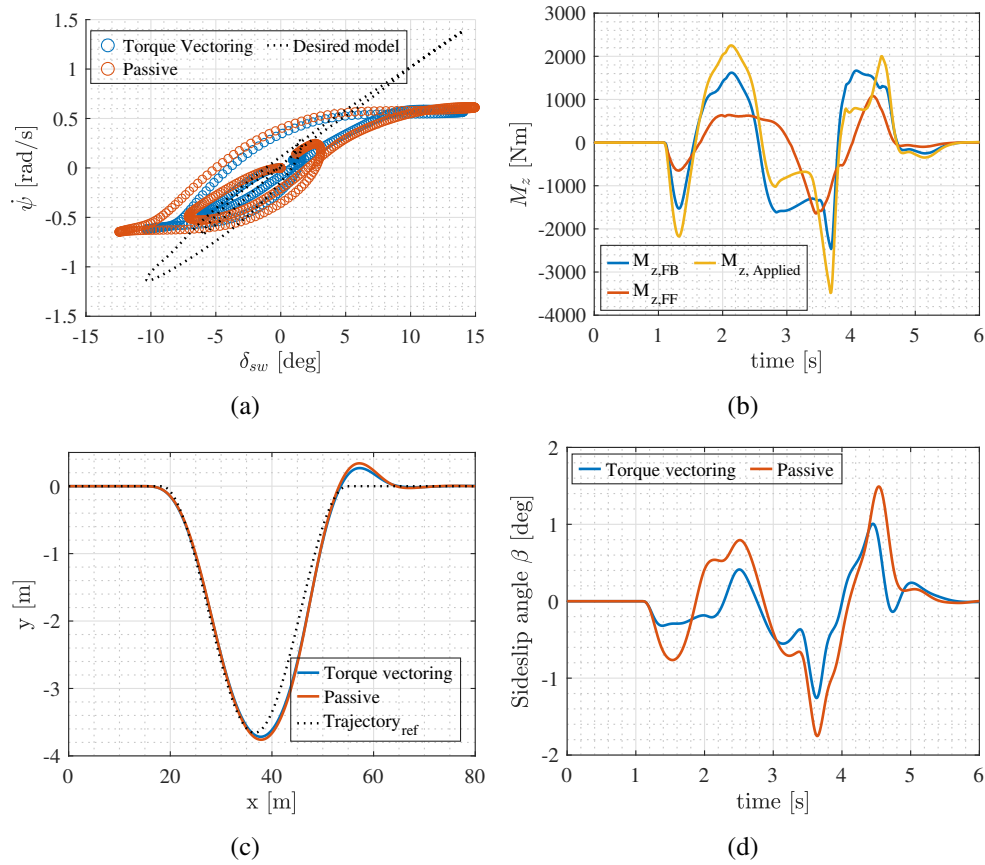


Fig. 4.10 DLC manoeuvre, 50 km/h, tight path, $\mu = 1$. Controlled = blue; passive = orange. (a) δ_{sw} vs. $\dot{\psi}$. (b) M_z vs. time. (c) Trajectory. (d) β vs. time.

4.4.3 Assessment of State Target Prediction

To assess the effect of the state targets prediction in the state feedback (Section 4.3.4), a DLC manoeuvre is simulated at 120 km/h under low friction conditions ($\mu = 0.5$). The passive vehicle cannot complete the manoeuvre due to loss of stability. Figure 4.11 compares two controller variants: one with predicted state targets, and one with fixed persistent targets. The predicted target formulation 4.3.4 reduces the sideslip and yaw rate deviations by up to 51% and 45%, respectively. The yaw moment is modulated faster and more smoothly. Steering effort is reduced with the predicted state targets, confirming the benefit of target evolution prediction.

4.4.4 Energy efficiency assessment

The energy efficiency benefits provided by the torque vectoring (TV) control system are evaluated through a dedicated case study: the in-wheel SUV of Case A, equipped (for this analysis only) with four identical in-wheel motors. The choice to simulate an all-wheel-drive configuration stems from the need for an overactuated powertrain architecture, which enables the implementation and evaluation of the energy-efficient torque allocation strategy.

Two maneuvers are considered for the analysis: a slow ramp steer at high friction conditions (μ), and a double lane change (DLC) at 120 km/h, as illustrated in Figure 4.11. For each case, the energy consumption of the passive configuration is compared with that of a baseline TV system employing a fixed 60/40 rear-to-front torque distribution, and with the energy-efficient allocator described in Section 4.3.7. As shown in Figure 4.12, the ECO allocator predominantly adopts an even 50/50 rear-to-front split throughout the maneuvers, introducing a slight rearward bias only when larger yaw moments are required. This behavior arises from the fact that the vehicle is equipped with four identical electric motors; thus, a balanced allocation minimizes power losses at the motor level. In scenarios requiring significant yaw moments, slip-related tire losses become dominant, and a rearward torque bias proves more efficient.

Tables 4.4.4 and 4.4.4 report the computed energy losses for each scenario. The powertrain losses are evaluated using the motor efficiency map presented in Figure 4.1. Longitudinal tire losses are computed according to Equation 4.59, while

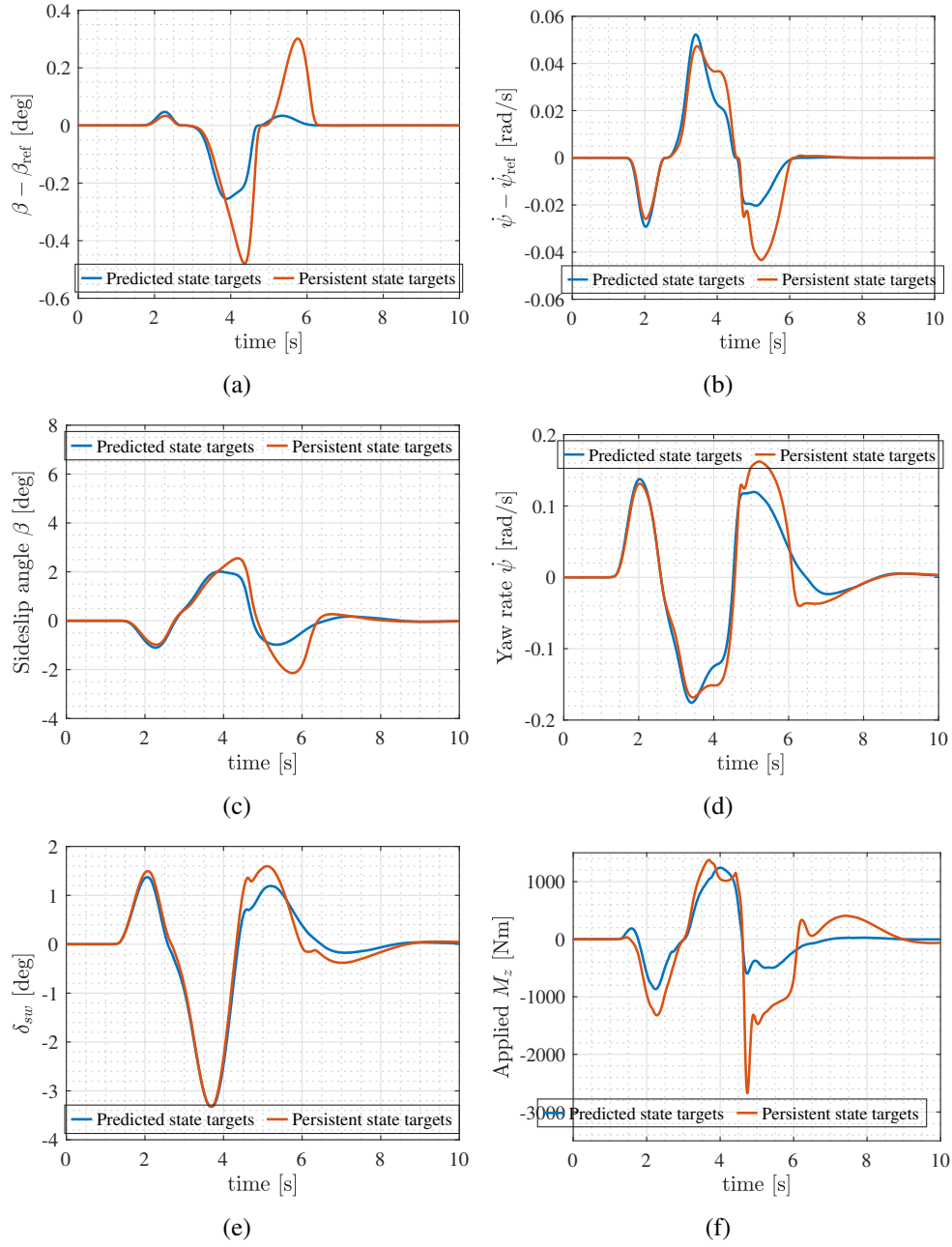


Fig. 4.11 DLC at 120 km/h, $\mu = 0.5$. Predicted vs persistent target vector configurations. a) β error. b) $\dot{\psi}$ error. c) β . d) $\dot{\psi}$. e) δ_{sw} . f) M_z .

lateral slip-induced dissipation is estimated as:

$$P_{\text{loss, tir. lat.}} = F_y \left(-v_x \cos \beta \pm \frac{t w_{F/R}}{2} \right) \sin \delta_i \pm (v_x \sin \beta + \dot{\psi} l_{F/R}) \cos \delta_i \quad (4.61)$$

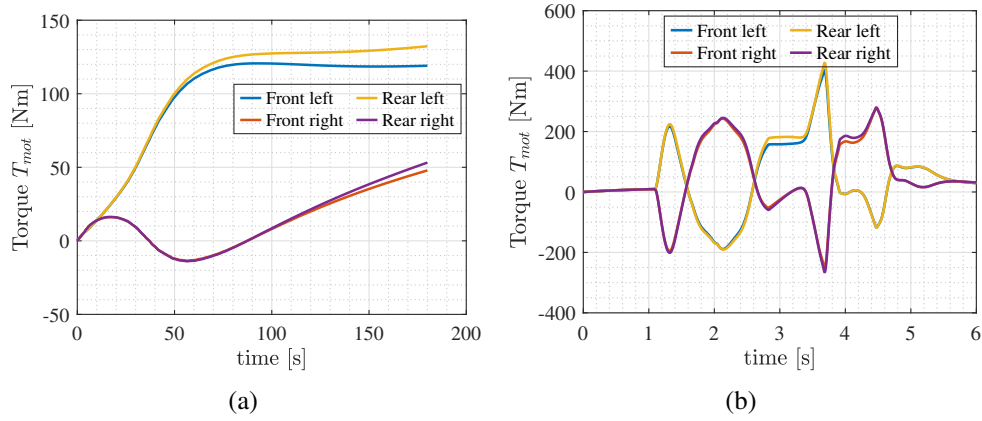


Fig. 4.12 Torque allocation for the Case A with equipped with 4 in-wheel motors, to evaluate the performance of the ECO allocator. (a) SRS high μ , and (b) DLC tight.

The results highlight that the TV control system leads to a net reduction in total energy losses, with the most significant contribution coming from reduced lateral tire slip dissipations, due to vehicle side slip angle reduction. In addition, by reducing the lateral slip of the tires, the TV controller is contributing to lowering the tire wear and the associated particulate matter (PM) emissions, a relevant environmental concern for battery electric vehicles, where non-exhaust sources dominate total PM output [154]. On the other hand, the ECO allocator further enhances motor efficiency and achieves a slight reduction in total energy consumption.

Table 4.3 Energy losses – SRS manoeuvre

	Longitudinal tire [Wh]	Lateral tire [Wh]	Powertrain [Wh]	Total [Wh]
Passive	2.03	2012	61.72	2075.75
TV	2.77	1566	60.42	1629.19
Eco allocator	2.15	1567	59.57	1628.72

Table 4.4 Energy losses – DLC manoeuvre

	Longitudinal tire [Wh]	Lateral tire [Wh]	Powertrain [Wh]	Total [Wh]
Passive	0.56	21.23	70.32	92.11
TV	0.62	18.70	70.48	89.80
Eco allocator	0.54	18.70	70.29	89.53

4.5 Experimental results

The experimental validation of the proposed torque vectoring control strategies was conducted on the SC24, the four-wheel-drive electric prototype developed by Squadra Corse PoliTo for the 2024 Formula Student season - the vehicle case study B, with the specifications reported in Table 4.2. The test campaign was carried out on a closed track, replicating typical racing manoeuvres, and focused on the evaluation of vehicle performance.

The control system hardware includes a dSPACE MicroAutoBox II, acting as the Vehicle Control Unit (VCU), which manages sensor data acquisition and command computation in real-time. The torque demands computed by the high-level control algorithms are sent via CAN to the four motor inverters. The control loop is executed at 1 kHz.

Vehicle state measurements rely on a set of high-fidelity sensors. The body dynamics are captured using an SBG Ellipse-N Inertial Measurement Unit (IMU), providing 3D acceleration and angular velocity data. Vehicle sideslip angle was measured during the experiments using a Kistler Correxit SF-Motion optical sensor, which provides direct non-intrusive measurement of longitudinal and lateral vehicle velocity components with high accuracy, aimed at the validation of the proposed sideslip angle estimation algorithm.

The logging architecture is based on the high-speed dSPACE data acquisition system, synchronised with the real-time control unit. This setup ensures precise timestamping of control variables and sensor data, enabling post-processing for control performance assessment. The overall system provides an integrated platform for experimental implementation, tuning, and driver/control influence evaluation.



Fig. 4.13 Squadra Corse Polito 2024 prototype during track testing session. Ground speed sensor installed on the rear of the vehicle.

4.5.1 Torque vectoring experimental validation

For each test condition, two configurations were evaluated: one with the proposed Torque vectoring algorithm enabled and the other with only the low-level baseline traction control system (TC) active, thus functioning passively. The selected maneuvers were analyzed through a set of relevant vehicle dynamics signals, which are plotted against distance.

The following signals were collected and analyzed:

- Driver steering input δ_{sw}
- Longitudinal vehicle speed measured by the Correvit SF-Motion sensor V_x
- Lateral acceleration from IMU sensor a_y
- Yaw rate from IMU sensor $\dot{\psi}$
- Sideslip angle β
- Yaw moment M_z commanded by the Torque Vectoring algorithm
- Motor torques commanded during TV operation T_{mot}
- GG-plot (longitudinal vs lateral acceleration) for a complete track lap

The performance was assessed through the following KPIs:

- Steering effort index $IACA_{\delta_{sw}}$, computed as in Equation 3.33
- Maximum steering angle $\delta_{sw,max}$
- Maximum lateral acceleration $a_{y,max}$
- Maximum sideslip angle β_{max}
- Yaw rate reference maximum error $\dot{\psi}_{err,max}$
- Yaw rate reference RMS error $\dot{\psi}_{err,rms}$
- Laptime t_{lap} (only for complete track laps)

Double lane change

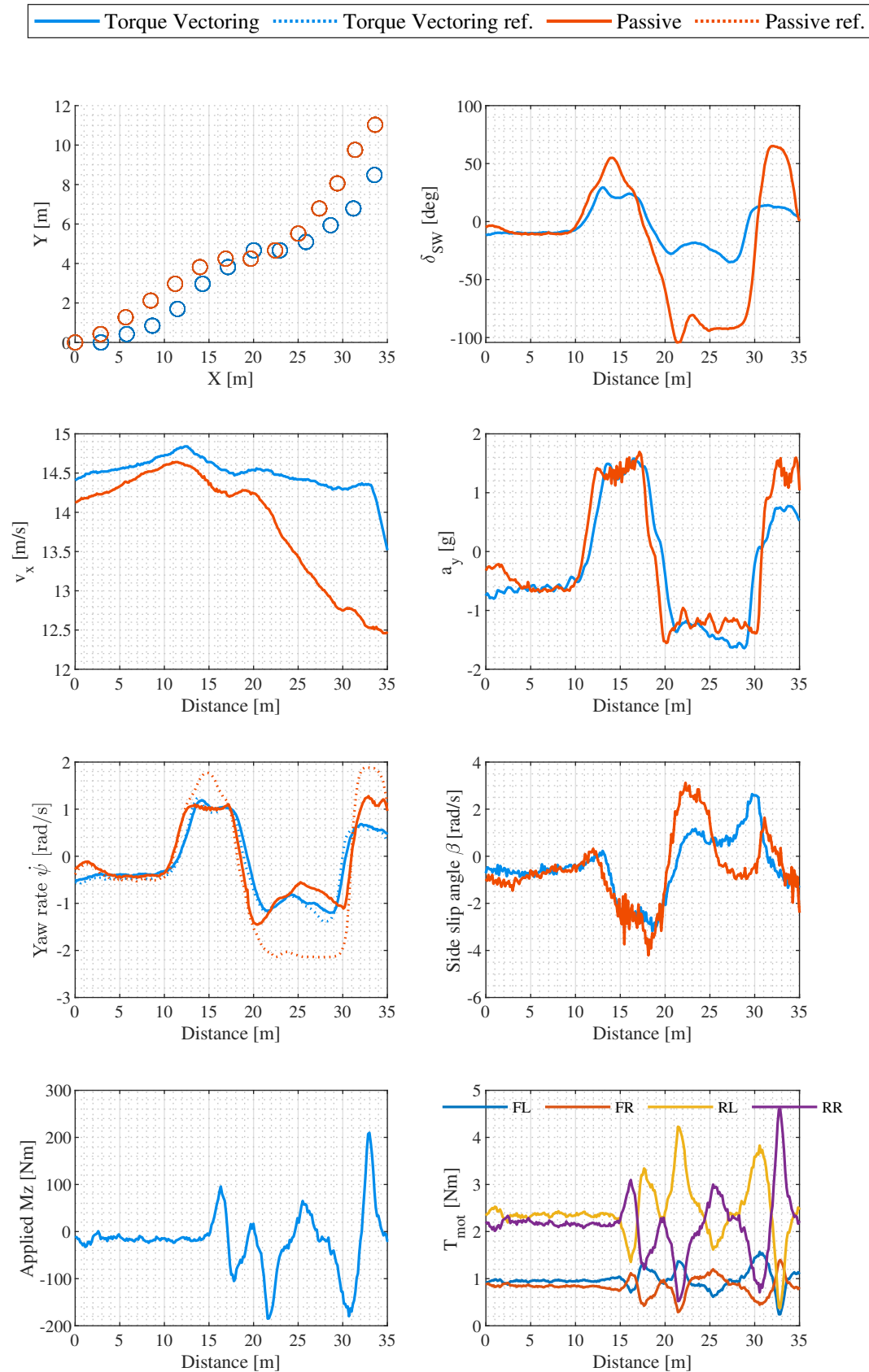


Fig. 4.14 Double lane change experimental test with case A vehicle - 4WD Formula student prototype.

The results reported in Figure 4.15 highlight the vehicle performance in transient lateral dynamic conditions, specifically during a DLC maneuver, and evaluate the benefits introduced by the proposed control system.

When the TV algorithm is enabled, a substantial reduction in steering effort is observed. This not only reduces the physical demand on the driver, but also contributes to enhanced vehicle stability. Notably, the front tire sideslip is significantly reduced, indicating a more linear tire behavior and operation away from the saturation region.

This improvement is mainly attributed to the accurate yaw rate tracking performance provided by the controller. The controller effectively generates the required yaw moment, allowing for smoother and more stable execution of the maneuver, with improved vehicle speed maintained throughout the test.

Overall, the DLC test confirms that the TV controller increases vehicle agility and responsiveness, while reducing the understeering tendency observed in the passive case. These outcomes are quantitatively supported by the KPIs reported in Table 4.5.

Table 4.5 KPI table for DLC maneuver

TV	$IACA_{\delta}$ [deg]	$\delta_{SW,max}$ [deg]	$a_{y,max}$ [g]	β_{max} [deg]	$\psi_{err,max}$ [rad/s]	$\psi_{err,rms}$ [rad/s]
OFF	37.15	104.3	1.69	4.21	1.57	0.67
ON	14.13	35.0	1.64	3.19	0.40	0.12

Track lap

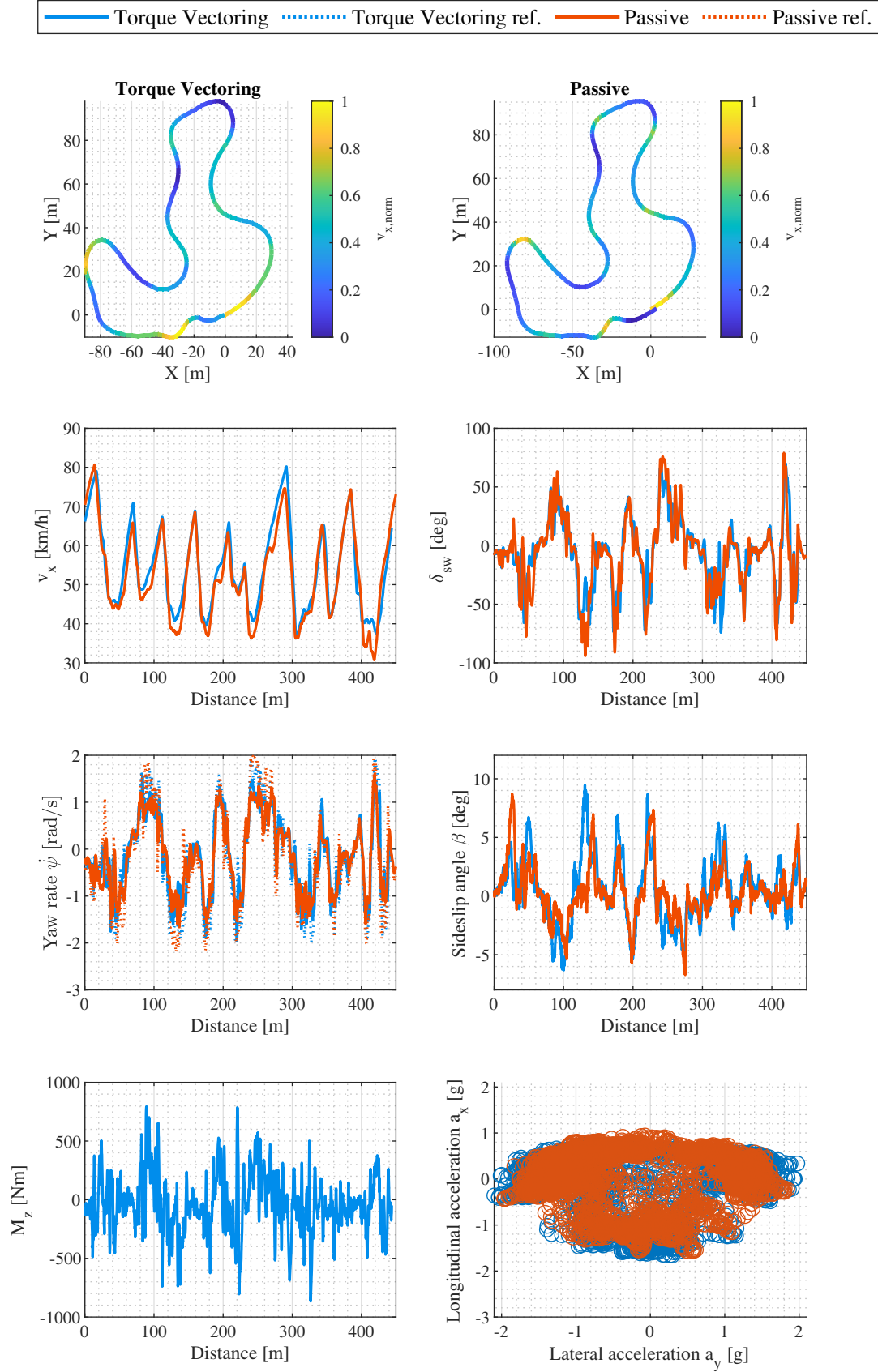


Fig. 4.15 Track lap experimental test with case A vehicle - 4WD Formula student prototype.

The analysis of the track lap results clearly demonstrates the effectiveness of the proposed control strategy in improving both vehicle handling and overall performance. The activation of the TV controller leads to an increase in the minimum speeds observed along the speed–distance profile, indicating a more efficient exploitation of grip.

From the GG-plot, it is evident that the peak lateral utilization zone is extended towards slightly higher longitudinal accelerations (up to 0.5 g). This enhancement enables the driver to apply throttle earlier during corner exits without exceeding the torque allocation or traction limits. Moreover, the presence of the controller reduces the risk of excessive wheel slip, thus allowing more aggressive braking and throttle inputs with improved safety margins. According to driver feedback, the maneuver becomes more intuitive and controllable, as the vehicle rotation can be managed through throttle modulation alone, with reduced risk of tire saturation.

Quantitatively, the benefit in lap time is significant: the controller enables a gain of approximately 1.4 s, corresponding to nearly 5% of the total lap time.

It is worth noting that the sideslip angle used as input to the TV controller corresponds to the measured value, not an estimated one. This choice does not affect the validity of the results, as during all tests the reference sideslip angle has remained equal to the measured one, given that sideslip regulation is only active for extreme conditions.

Table 4.6 KPI table for track lap

TV	IACA_δ [deg]	$\delta_{\text{SW,max}}$ [deg]	$a_{y,\text{max}}$ [g]	β_{max} [deg]	$\psi_{\text{err,max}}$ [rad/s]	$\psi_{\text{err,rms}}$ [rad/s]	T_{lap} [s]
OFF	26.08	94.0	1.96	8.71	1.28	0.40	32.19
ON	24.52	74.1	2.10	9.46	1.13	0.34	30.79

4.5.2 Sideslip angle estimation experimental validation

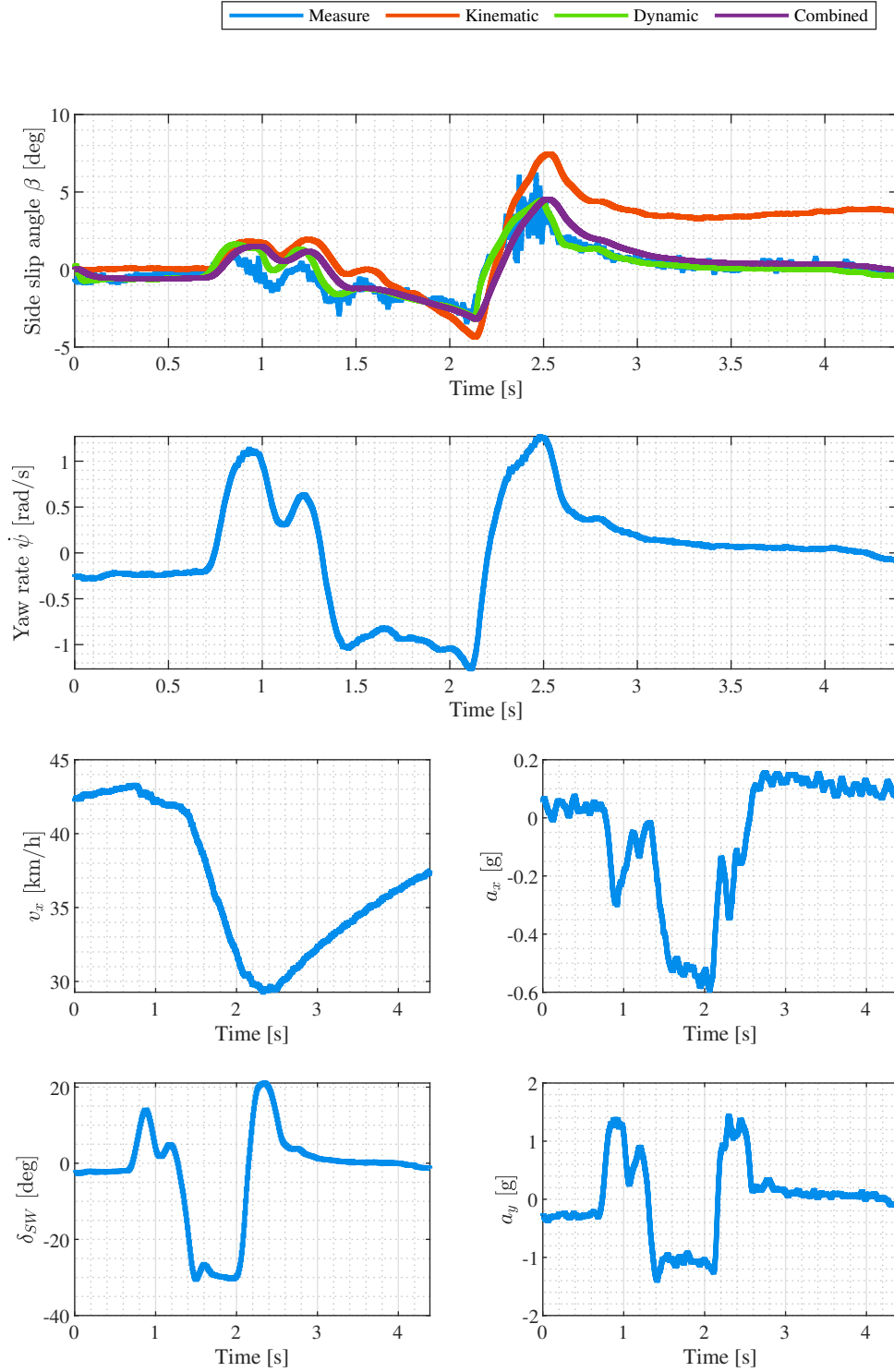


Fig. 4.16 Sideslip angle estimation algorithm experimental validation, DLC test.

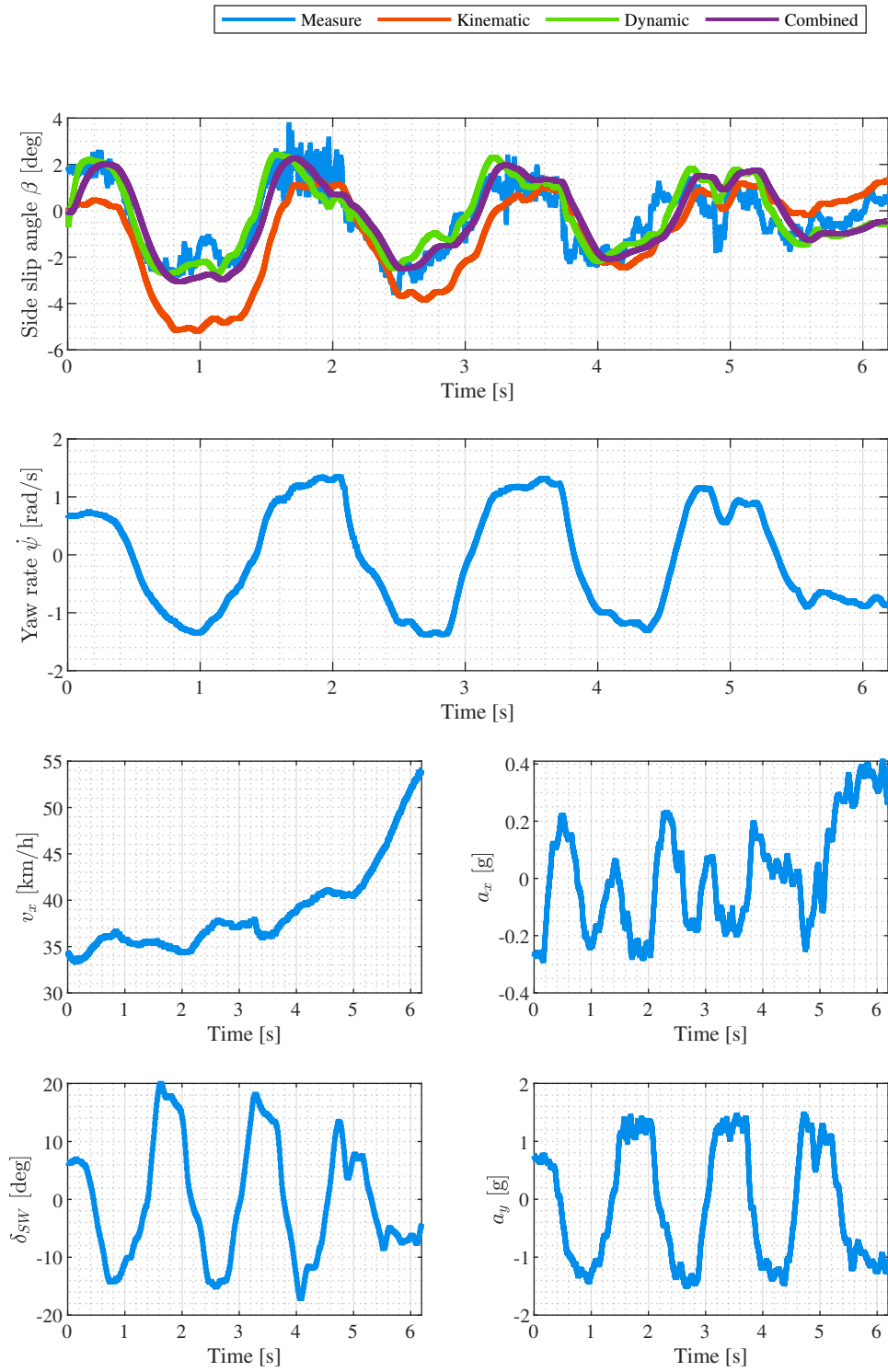


Fig. 4.17 Sideslip angle estimation algorithm experimental validation, slalom test.

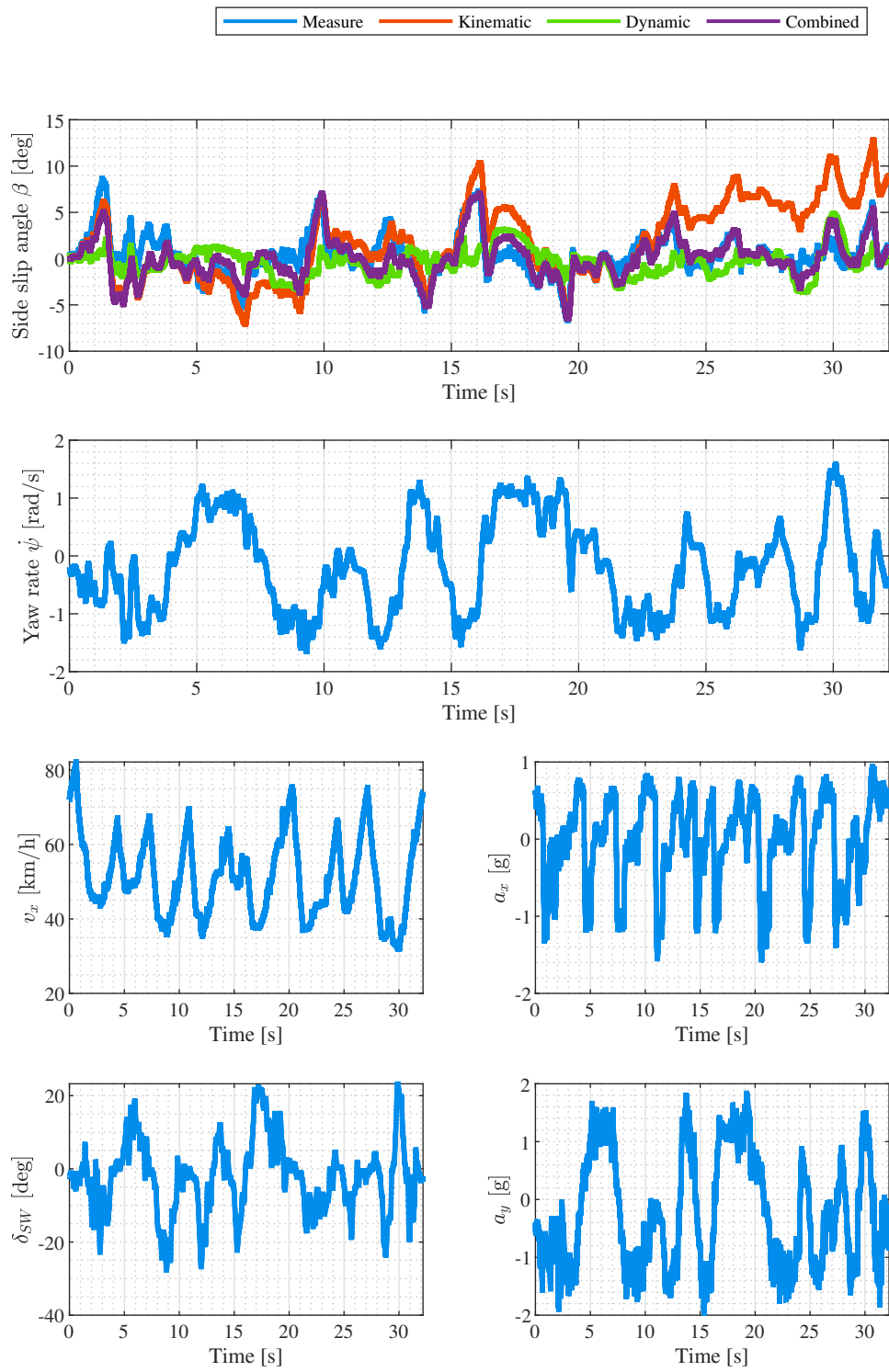


Fig. 4.18 Sideslip angle estimation algorithm experimental validation, track-lap test.

The proposed state-feedback TV controller relies on the availability of the vehicle sideslip angle β . To this end, a combined model- and kinematics-based estimation algorithm (described in Section 4.3.5) has been implemented and validated under track conditions.

For validation purposes, the measured sideslip angle from a Kistler ground speed sensor is used as ground truth, while the estimation algorithm runs in real-time on the dSPACE control unit. The estimated signal is compared against three approaches: a purely kinematic method, a purely model-based approach (labelled as dynamic), and the proposed combined estimator, following the methodology outlined in [155].

The performance of the estimation algorithm is evaluated across multiple scenarios: a double lane change maneuver (Figure 4.16), a constant-speed slalom (Figure 4.17), and a complete track lap (Figure 4.18). These tests are intended to validate the estimator's accuracy and robustness across a variety of dynamic conditions and vehicle operating points.

The evaluation of sideslip angle estimation across the three maneuvers confirms the expected behavior of each estimator depending on the dynamic conditions of the vehicle, as reported in Table 4.7. The kinematic approach, which relies only on sensor-based quantities, shows poor performance in all cases, especially during the DLC and slalom, where sensor bias and integration drift significantly affect the accuracy, resulting in high RMS and peak errors.

The dynamic estimator performs substantially better, especially in the slalom maneuver, where the vehicle undergoes quasi-steady lateral motion with reduced longitudinal excitations. Under these conditions, the internal model, despite its simplifications, remains valid, and the estimation is robust against sensor noise.

The combined estimator consistently provides good overall performance in all scenarios, achieving the lowest RMS and peak errors in the track lap scenario. Its advantage lies in the complementary nature of the two sources: the kinematic part ensures better tracking of high-frequency variations, while the dynamic part stabilizes the estimation over longer time horizons.

Overall, the combined approach offers the best compromise across a wide range of operating conditions, confirming its suitability for real-time implementation in track environments.

Table 4.7 Sideslip angle estimation performance for selected maneuvers

Maneuver	Max Absolute Error [deg]			RMS Error [deg]		
	Kinematic	Dynamic	Combined	Kinematic	Dynamic	Combined
DLC	5.44	2.82	3.39	2.49	0.51	0.81
Slalom	3.85	2.94	3.02	1.5	0.74	0.90
Lap	9.98	7.98	5.85	3.78	2.72	1.53

4.6 Concluding remarks

Multi-motor electric vehicle architectures enable the implementation of advanced torque vectoring strategies, leveraging independent wheel actuation to enhance vehicle dynamics. In this context, a novel torque vectoring algorithm has been proposed, combining a model-based feedforward component with an adaptive predictive state-feedback controller. The latter integrates vehicle handling constraints directly into the cost function of the optimal control problem, thereby avoiding explicit inequality constraints and improving computational efficiency.

The proposed TV algorithm was first evaluated through simulation on a rear-wheel-drive electric vehicle equipped with in-wheel motors. The results highlight the benefits of predictive control formulations in anticipating and regulating vehicle states near the handling limits, improving agility and stability.

Experimental validation was then conducted on a four-wheel-drive Formula Student vehicle with in-wheel motors, confirming the algorithm's effectiveness in real-world conditions. The tests demonstrated improved responsiveness and controllability, particularly in transient maneuvers such as double lane changes and full-lap driving, while maintaining high stability margins.

Additionally, an energy-efficient torque allocation strategy for four-motor configurations was proposed and assessed via simulation.

Finally, a combined sideslip angle estimation algorithm, based on the fusion of kinematic and dynamic models, was implemented and validated experimentally. The estimator exhibited robust performance across various maneuvers, confirming its suitability for real-time applications in torque vectoring control architectures.

Chapter 5

Conclusions and future works

5.1 Conclusions

This doctoral thesis investigated novel design and control methodologies for electric traction systems, aiming to enhance both energy efficiency, handling, and safety performance of battery electric vehicles (BEVs). The work was structured around three main areas: optimal design of an innovative low-voltage reconfigurable electric drive module, development of a pre-emptive traction control system, and design of advanced torque vectoring strategies for multi-motor powertrains.

To address the research questions introduced in Chapter 1, the following conclusions can be drawn:

- The proposed modular low-voltage vehicle architecture enables a flexible solution to urban and extra-urban driving needs. The design of a dual-inverter, multi-phase EDM, integrated with swappable battery modules, demonstrates the feasibility of a scalable and reconfigurable solution compliant with L-category voltage limits, while achieving M-category performance targets.
- A multi-objective design methodology based on driving-cycle optimization was developed and successfully applied to an IPM machine. The use of a MOGA enabled the identification of an optimal trade-off between efficiency, material cost, and torque capability across both urban and mixed driving conditions. The methodology integrated electromagnetic, mechanical, and thermal constraints via FEM-based simulations.

- A novel preview-based nonlinear model predictive controller (NMPC) was developed for traction control, incorporating road profile and friction information. Simulation and experimental tests showed that the proposed controller significantly improves longitudinal slip regulation, especially in low-friction and irregular road conditions, outperforming benchmark SMC and state-of-the-art MPC solutions. The performance of the controller is evaluated on different electric motor responses to highlight the new possibilities in optimal torque control provided by electric traction systems.
- Predictive torque vectoring control strategies were proposed and validated for dual- and quad-motor architectures, using both simulation and track testing. The strategies showed benefits in agility, stability, and efficiency, demonstrating the potential of powertrain-based chassis control. An energy-aware allocation algorithm further enabled loss minimization without compromising vehicle dynamics. Non-measurable variables estimation algorithms are proposed and experimentally tested, to further validate the feasibility of the complete control framework.

Overall, the results confirm that electric powertrains, when optimized in both their architecture and control logic, offer new degrees of freedom to enhance performance, energy consumption, and user-centered applications.

5.2 Future Works

Building upon the promising outcomes of this research, several directions are proposed for future development:

- **Experimental validation of the designed EDM:** The designed six-phase IPM motor and dual-inverter system will be assembled and tested under real-world conditions. Static and dynamic test campaigns will validate the FEM-based predictions and thermal network models presented in Chapter 2. A full scale vehicle prototype will be used to assess the performance at the vehicle level. Furthermore the concept of modular vehicle can be extended to other use cases, integrating a higher number of modules, and different mission profiles.

- **Integrated energy management:** A supervisory control strategy will be developed to coordinate energy flow between the two battery modules, enabling differential power split. Exploiting asymmetric current sharing between the two three-phase subsystems could support fault tolerance, regenerative balancing, and range performance optimization.
- **Artificial intelligence for vehicle dynamics control:** Advanced AI-based models could be trained to estimate non-measurable states and to preview road conditions. Deep neural networks can be implemented to reduce the number of onboard sensors and enhance the scalability of the control system. Imitation learning techniques will be trained based on the NMPC behavior and deployed on the vehicle's control unit to reduce the computational demand of the control system.
- **Integrated control strategies:** Modern vehicles are increasingly equipped with multiple chassis actuators, including active suspensions, rear-wheel steering systems, and active kinematics or camber control. These systems independently contribute to ride comfort, handling, and stability. However, their potential is often limited by uncoordinated control logics. Future research will investigate the development of a centralized high-level controller capable of integrating torque vectoring with other chassis actuation domains. A unified control strategy would coordinate longitudinal, lateral, and vertical dynamics in real time, maximizing vehicle performance and safety across various driving scenarios. Model predictive control (MPC) or hierarchical optimization schemes could be employed to resolve actuator redundancy and manage trade-offs between agility, comfort, and energy efficiency.
- **Additional use cases for ECO TV:** A promising direction is the investigation of asymmetric motor layouts—such as one rear motor and two independent front motors. This setup provides a more representative scenario to test the capabilities of the proposed energy-aware torque allocation algorithm (ECO allocator), as it enables the coordination of multiple motors with different efficiency characteristics and constraints. Such a case study would allow a more in-depth evaluation of energy distribution strategies and highlight the scalability of the proposed control approach to heterogeneous multi-motor powertrains.

This thesis provides a foundation for the development of a new generation of electric powertrains that combine high efficiency, adaptability, and intelligent control. By integrating optimization techniques into both design and control stages, it demonstrates how electrification not only enables superior torque actuation and energy efficiency, but also opens the way to modular and reconfigurable architectures tailored to diverse user needs. These technological advances can foster the growth of novel mobility systems, flexible, safe, performative, and user-centered, which are crucial to accelerate the diffusion of electrified vehicles and overcome current barriers such as cost, range anxiety, and infrastructure limitations. In this perspective, the proposed methods and case studies contribute to shaping more accessible and sustainable electric mobility ecosystems.

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